Meta-XNLG: A Meta-Learning Approach Based on Language Clustering for Zero-Shot Cross-Lingual Transfer and Generation

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Abstract

Recently, the NLP community has witnessed a rapid advancement in multilingual and cross-lingual transfer research where the supervision is transferred from high-resource languages (HRLs) to low-resource languages (LRLs). However, the cross-lingual transfer is not uniform across languages, particularly in the zero-shot setting. Towards this goal, one promising research direction is to learn shareable structures across multiple tasks with limited annotated data. The downstream multilingual applications may benefit from such a learning setup as most of the languages across the globe are low-resource and share some structures with other languages. In this paper, we propose a novel meta-learning framework (called Meta-XNLG) to learn shareable structures from typologically diverse languages based on meta-learning and language clustering. This is a step towards uniform cross-lingual transfer for unseen languages. We first cluster the languages based on language representations and identify the centroid language of each cluster. Then, a meta-learning algorithm is trained with all centroid languages and evaluated on the other languages in the zero-shot setting. We demonstrate the effectiveness of this modeling on two NLG tasks (Abstractive Text Summarization and Question Generation), 5 popular datasets and 30 typologically diverse languages. Consistent improvements over strong baselines demonstrate the efficacy of the proposed framework. We observe that zero-shot XNLG for low-resource languages is the first attempt to study meta-learning techniques for cross-lingual natural language generation (XNLG). Particularly, we focus on zero-shot XNLG for low-resource languages. Unlike NLU tasks, we observe that zero-shot NLG is a more

1https://www.ethnologue.com/statistics

1 Introduction

There are more than 7000 known living languages across the globe. 95% of the world’s population does not speak English as their first language and 75% does not speak English at all\(^1\). Most of the languages are low-resource languages as they do not have adequate resources for natural language processing research (Joshi et al., 2020). On the other hand, a vast majority of studies in NLP research are conducted on English data (Bender, 2019). To democratize the NLP research for the benefit of the large global community, it is essential to focus on the non-English languages. However, creating/collcetring task-specific annotated data for all the languages is expensive and time-consuming. Moreover, human languages are dynamic as new words and domains are added continuously. An alternate solution is to investigate NLP modeling techniques that allow to train the model with high-resource languages like English and transfer supervision to low-resource languages (with limited annotated data) or unseen languages for several NLP applications. Recently, there has been promising progress on cross-lingual transfer learning research (Hu et al., 2020; Artetxe et al., 2020) but supervision transfer is uneven across languages which leads to large performance gaps. Such performance gaps are observed because models do not account for cultural and linguistic differences in the modeling (Lai et al., 2019; Blasi et al., 2021). This paper is a step towards bridging this gap via meta-learning and language clustering.

Meta-learning or learning to learn (Bengio et al., 1990) is a learning paradigm where the model is trained on diverse tasks and quickly adapts to new tasks given a handful of examples. It has emerged as a promising technique for Machine Learning (Finn et al., 2017; Koch et al., 2015), Natural Language Understanding (Murty et al., 2021; Yan et al., 2020) and Machine Translation (Gu et al., 2018) tasks. This work - to the best of our knowledge - is the first attempt to study meta-learning techniques for cross-lingual natural language generation (XNLG). Particularly, we focus on zero-shot XNLG for low-resource languages. Unlike NLU tasks, we observe that zero-shot NLG is a more
challenging setup as text should be generated in unseen languages (which often suffers from accidental translation (AT) problem (Xue et al., 2021)) and is expected to be grammatically coherent, semantically correct and fluent. We aim to address the following research problem: Does meta-learning algorithm trained on typologically diverse languages (as training task) provide language-agnostic initialization for the zero-shot cross-lingual generation? Our main contributions in this work are listed below:

- We propose Meta-X\textsubscript{NLG}, a framework for effective cross-lingual transfer and generation based on Model-Agnostic Meta-Learning (MAML) algorithm.
- We use language clustering to identify a set of meta-training languages, which provides a more uniform cross-lingual transfer to unseen languages.
- We test Meta-X\textsubscript{NLG} on two NLG tasks (Abstractive Text Summarization and Question Generation), five popular datasets (XL-Sum, Wikilingua, MLQA, TyDiQA and XQuAD) and 30 languages. We observe consistent improvement over strong baselines involving mT5.
- We show an effective zero-shot X\textsubscript{NLG} modeling setup, which is less vulnerable to the accidental translation problem.

2 Related Work

We focus on two threads of related work in this section: (1) cross-lingual generation and (2) meta-learning for NLP. Traditional approaches for cross-lingual generation use machine translation (MT) in the modelling pipeline (Wan et al., 2010; Ayana et al., 2018; Duan et al., 2019). Such approaches have an inherent problem as translations are generally error-prone. The errors are more when at least one of the languages involved in the translation is a low-resource language. Recently cross-lingual transfer approaches are gaining attention. These methods use parallel data (Chi et al., 2020a) and small annotated datasets (Kumar et al., 2019) in zero-shot and few-shot cross-lingual generation respectively. Lewis et al. (2020a) fine-tune a pre-trained model with multiple low-resource languages and evaluate on a single target language in zero-shot setting. In the same line of research, Maurya et al. (2021) modified mBART pre-trained model with an unsupervised dataset involving monolingual data in three languages for cross-lingual transfer. This model, called ZmBART, is tested on a small set of languages - English, Hindi and Japanese. Moreover, it has been observed that such cross-lingual transfers are not uniform across the languages (Lin et al., 2019; Blasi et al., 2021).

Recently, meta-learning has been actively applied for many NLP applications (Bansal et al., 2020; Gao et al., 2019) and also for NLU tasks such as text classification (van der Heijden et al., 2021), NER (Wu et al., 2020), task-oriented dialogue and QA (M’hamdi et al., 2021), etc. Tarunesh et al. (2021) propose joint meta-learning approach on multiple languages and tasks from XTREME benchmark (Hu et al., 2020). Close to our work, Nooralahzadeh et al. (2020) propose a meta-learning approach for cross-lingual transfer on NLI and QA, both NLU tasks. The authors use one or two randomly selected languages for meta-training. In contrast, we provide a systematic approach based on language clustering to identify the right meta-training languages. Moreover, to the best of our knowledge, ours is the first effort that employs meta-learning for natural language generation.

3 Meta-Learning Algorithm: MAML

Meta-learning tries to learn structure among multiple tasks such that the new tasks are adapted quickly given few training instances. Among several meta-learning algorithms, we focus on optimization-based algorithms, i.e., Model Agnostic Meta-Learning (MAML) (Finn et al., 2017) due to its recent success in multiple NLP and computer vision tasks. MAML progresses in two phases: meta-training and adaptation. In the meta-training phase, the model learns a good initialization of parameter values by repeatedly simulating the learning process on training tasks. In the adaptation phase, these learned parameters are quickly adapted to new tasks. The underlying constraint is that all tasks should share some common structure (or come from a task distribution). The world’s different languages follow this constraint as they came into existence with a common goal of communication, and share some structure. For meta-learning purposes, we treat them as different tasks.
Unlike traditional machine learning, meta-learning has meta-train and meta-test data splits for meta-training and adaptation respectively. Each split consists of tasks that are sampled from a distribution \( p(D) \) over task datasets \( \{D_1, D_2, \ldots, D_n\} \) where \( D_i \) is associated with \( i^{th} \) task \( T_i \). Each \( D_i \) has support set and query set \( D_i = \{S_i, Q_i\} \). Support set and Query set are analogous to train and test splits of the traditional machine learning. We use \( f_\theta \) to denote a neural network model parameterized by \( \theta \).

Meta-training has two-levels of optimization: inner-loop optimization and outer-loop optimization. In the inner-loop optimization, for each sampled task \( T_i \), the task-specific model parameters \( \theta^* \) are updated by \( m \) iterations of stochastic gradient descent (SGD) with support set \( S_i \). The overall model parameters \( \theta \) are learned to optimize the performance of models \( f_{\theta^*} \) on query sets \( Q_i \) across datasets \( p(D) \) in the outer-loop optimization. The MAML (Finn et al., 2017) objective is:

\[
\theta^* = \arg \min_\theta \sum_{D_i \sim p(D)} L_i(f_{\theta^*}(m))
\]

(1)

where \( L_i(f_{\theta^*}(m)) \) is the loss obtained on query set for task \( T_i \) and \( f_{\theta^*}(m) \) is obtained after \( m \) iteration of SGD update with Task \( T_i \) as:

\[
f_{\theta^*}(m) = f_\theta - \alpha \nabla_\theta L_i(f_\theta)
\]

In outer-loop optimization, MAML performs MetaUpdate which a batch as:

\[
\theta = \theta - \beta \nabla_\theta \sum_{D_i \sim p(D)} L_i(f_{\theta^*}(m))
\]

(2)

Where \( \alpha \) is inner-loop learning rate and \( \beta \) is meta (outer-loop) learning rate. In the adaptation phase, the model is initialized with learned optimal meta-parameters \( \theta^* \), which is updated by a few steps of SGD with a support set (aka. few-shot learning) and directly evaluated on the query set of the meta-test dataset. Our aim is to perform zero-shot evaluation, so we skip the adaptation phase and directly evaluate the learned model on meta-test datasets.

4 Methodology

In the proposed Meta-XSLG framework, we first cluster the available languages and identify the centroid languages. Then we train a model with MAML on centroid languages to obtain an optimal initialization of parameters. Finally, the learned model is deployed to generate text in the zero-shot setting. Figure-1 provides an overview of proposed framework. We now provide details of each component of the framework.

4.1 Language Clustering

Broadly, the languages can be clustered in two ways: (1) By language family consideration and (2) By exploiting similarities among learned language representations. To learn language representations, Littell et al. (2017) used typological information from linguistic knowledge-bases like WALS (Dryer and Haspelmath, 2013) Glottolog (Hammarström et al., 2017), etc. Malaviya et al. (2017) extract learned language tag representations from tasks like machine translation. Recently, Oncayev et al. (2020) fuse typologically learned and task-learned language representations using singular vector canonical correlation (SVCC) analysis to obtain multi-view language representation. Further, the authors cluster languages using this rich multi-view language representations through hierarchical clustering.

We utilize this clustering approach in our proposed framework.

Next, we aim to identify a representative language (centroid language) for each cluster. Formally, given a cluster \( C = \{L_1, L_2, \ldots, L_t\} \), where each \( L_i \) is multi-view representation of \( i^{th} \) language, the centroid language \( L^*_t \in C \) is defined as:

\[
L^*_t = \arg \min_{L_t \in C} \sum_{L_j \in C} d(L_j, L_t).
\]

(3)

We use \( d \) as the cosine distance. In the proposed meta-learning algorithm, the centroid languages act as Meta-Training tasks/languages and the rest of the non-centroid languages across clusters act as Target (aka. evaluation) tasks/languages. In this setup, the best performing model should hold two properties i.e., Intra-cluster Generalization and Inter-cluster Generalization. In the proposed framework, training with a centroid language leads to better transfer capability within cluster, and using multiple centroid languages extend the transfer capability to multiple closely-knit clusters and increase coverage. In this way the stated properties can be achieved.

However, there is a trade-off between the number of clusters (the number of meta-training languages) and generalization. If there is a single
cluster (a single meta-training language), then the model tries to over-generalize for different typological structures and fails in the attempt. On the other extreme, if there are too many centroid languages (many typologically diverse structures in meta-training), then the learning possibly gets distracted. In both cases, the model will be unable to learn a reasonable structure (the required generalization) and perform poorly. Section-6.2 consists discussions and empirical evidence. Our experiments suggest that three clusters across considered languages provide the best performance. These three clusters are always fixed irrespective of the datasets and underlying tasks. Composition of the clusters (with three clusters) are shown in Table-1. See Figure-3 for more details on the clustering.

4.2 Meta-XNLG Training

The framework consists of five training steps: Selection of Base Pre-trained model, Adaptive unsupervised pre-training, Fine-tuning with HRL, Meta-training with LRLs, and Meta-adaptation for Zero-shot. The motivation and details of each step are included below:

1. Selection of Base Pre-trained Model ($P_M$): Our approach is model-agnostic, therefore any state-of-the-art sequence-to-sequence multilingual pre-trained language model ($P_M$; like mBART, mT5, etc.) can be used. We selected mT5 due to its superiority on many NLP tasks (Xue et al., 2021).

2. Adaptive Unsupervised Pre-training ($ZP_M$): Zero-shot cross-lingual generation often suffers from accidental translation (Xue et al., 2021) and other generation problems. To overcome this, we further train $P_M$ on a MultiMonoLang corpus with mT5 denoising objective. We created MultiMonoLang corpus by concatenating small unsupervised samples from each of the 30 languages. We call this model $ZP_M$ (or ZmT5). See section-4.3 for more details.

3. Fine-tuning $ZP_M$ on High Resource Language (i.e., English): It is often observed that downstream LRLs applications benefit when supervision is transferred from HRL (Hu et al., 2020). Following the trend, we fine-tune the $ZP_M$ model with the task-specific English data and call this model as $EnZP_M$ with parameters $\theta_p$.

4. Meta-Training with Low-resource Centroid Languages: We use the validation sets of each centroid language as the meta-train dataset. The meta-learner is initialized with the $EnZP_M$ parameters. Then, a batch of tasks/languages $T_i$ and corresponding datasets $D_i$ are randomly sampled. Further, each $D_i$ is equally split into support set $S_i$ and query set $Q_i$ such that they are mutually exclusive. $m$-step gradient update is done in the inner-loop using $S_i$. This is repeated for all the training tasks. Finally Meta-Update is done using mean loss computed on $Q_i$ as shown in Equation 2. This is repeated for all the tasks/languages over multiple batches. The batches are sampled uniformly across all centroid languages. The formal description is shown in Algorithm-1.

5. Meta-adaptation for Zero-shot Evaluation: The meta-learned model $f_{\theta^*}$ from the previous step can be directly evaluated on the test sets of the target languages in zero-shot evaluation. The proposed framework can be easily extended to few-shot setting. In this setting, the meta-learned model can be fine-tuned on a small number of validation set examples with standard supervised learning and evaluated on the test sets.
of target languages. In this work we consider zero-shot setting only.

Algorithm 1 Meta Learning Algorithm

Require: Task set distribution \( p(D) \), pre-trained model \( E_{\theta} Z P_M (P) \) with parameters \( \theta_P \), meta-learner \( f_\theta \) with parameter \( \theta \).

Require: \( \alpha, \beta \): step size hyper-parameters
1: Initialize \( \theta \leftarrow \theta_P \)
2: while not done do
3: Sample batch of tasks \( T = T_1, T_2, \ldots T_b \sim p(D) \)
4: for all \( T_i \) in \( T \) do
5: Initialize \( \theta_i \leftarrow \theta \)
6: Split \( D_i \) to form support set \( S_i \) and query set \( Q_i \)
7: for all inner_iter steps \( m \) do
8: Compute \( \nabla_{\theta_i} L_{T_i}^S(P_{\theta_i}^{(m)}) \)
9: Do SGD: \( \theta_i^{m+1} = \theta_i^m - \alpha \nabla_{\theta_i} L_{T_i}^S(P_{\theta_i}^{(m)}) \)
10: end for
11: MetaUpdate: \( \theta = \theta - \beta \nabla_\theta \sum_{i=1}^b L_{T_i}^Q(P_{\theta_i}^{(m)}) \)
12: end for
13: end while
14: Do zero-shot/few-shot learning with meta-learner \( f_\theta \), where \( \theta^* \) is learned optimal parameters of meta-learner.

4.3 Avoiding Accidental Translations: It has been observed that popular pre-trained models like mBART and mT5 suffer in well-formed generation for unseen low-resource (zero-shot) languages. Broadly, they suffer from Accidental Translation (AT), where the model generates whole/part of the output in the fine-tuning language (Xue et al., 2021). This happens when the model forgets the learning obtained before fine-tuning. This is analogous to the Catastrophic-Forgetting problem (Chi et al., 2020a) in multi-task setup, where the model forgets the learnings about the previous task. For language generation, this also leads to problems like improper predictions, structural and normalization errors, etc., as the different languages differ in morphology, phonology, subject-verb-object ordering, etc.

To mitigate/reduce these problems, Xue et al. (2021) suggested mixing a small amount of multilingual pre-training task data into the fine-tuning stage. However, it is unclear what ratio mixing should be done and how this joint training will affect generation quality. Moreover, such mixing is not a feasible solution for multi-level fine-tuning (as in our proposed setup - English fine-tuning then meta-training with centroid languages). Inspired from Maurya et al. (2021), the following solution approach are adopted in Meta-XNLG framework.

• Adding Language Tag: We concatenate \(<fxx> \) where \( xx \) is language code as per ISO 693-2 standard.

• Adaptive Unsupervised Pre-training: Further train the base pre-trained model on Multi-MonoLang corpus with denoising language model objective. Unlike Maurya et al. (2021), we use mT5 denoising objective (Xue et al., 2021) instead rand-summary objective which leads to better performance.

• Freezing model Components: One of the key approaches to mitigate CF problem is freezing model parameters. Maurya et al. (2021) performed an ablation study and concluded that freezing all token embeddings and decoder parameters of the model work best. We adapted these findings while English-fine tuning and meta-training steps.

We observed that the above settings work better to mitigate (or reduce) the AT problem. See Table-12 in appendix for ablation study results.

5 Experiment Setup
We investigate Meta-XNLG’s performance on two NLG tasks, five datasets and 30 languages. mT5 pre-trained model is used as the base model. The model performance is compared with two strong baselines in zero-shot setting.

5.1 Tasks and Datasets

5.1.1 Abstractive Text Summarization (ATS): ATS is the task of generating grammatically coherent, semantically correct and abstractive summary given an input document. We use two publicly available datasets: XL-Sum (Hasan et al., 2021) and Wikilingua (Ladhak et al., 2020). XL-Sum is a large comprehensive dataset where article-summary pairs are extracted from BBC and annotated by professional annotators. It covers 44 languages including very low-resource languages like Nepali and Swahili. Due to computational limitation, we consider only 23 languages. Wikilingua is a large-scale dataset covering 18 languages. Article and summary pairs are extracted from WikiHow\(^3\). It is how-to guides on diverse topics written by human annotators. We consider all 18 languages in our experiments.

5.1.2 Question Generation (QG):
In QG, given an input passage and an answer, it aims to generate semantically and syntactically

\(^3\)https://www.wikihow.com/
We concatenated Wikipedia articles in multiple languages which XQuAD does not have any English training data. Follow similar goals and have same format. In this way we have 7 datasets for 7 languages. 

MLQA is a multi-way parallel extractive QA evaluation dataset available in 7 languages. Authors automatically extracted paragraphs from Wikipedia articles in multiple languages which have same or similar meaning. Authors crowdsource questions on English and translate into target languages by professional translators. As our framework is based on supervision transfer we only consider the evaluation data instance where input and target text languages are same. In this way we have 7 datasets for 7 languages.

XQuAD dataset is translated from the development set of SQuAD v1.1 (Rajpurkar et al., 2016) by professional human translators into 10 languages. Each language has 1190 question-answer pairs. SQuAD is popular question answering dataset consisting of around 100k <passage, question, answer> triplets. We added additional Japanese language dataset (Takahashi et al., 2019) which is created with similar goals and has same format.

TyDiQA is another QA dataset with 204K question-answer pairs in 11 typologically diverse languages. Unlike MLQA and XQuAD, it is directly collected in each language and does not involve any translation. We use, TyDiQA-GoldP datasets which is guaranteed to have extractive nature. We added Tamil as additional language that share same format and created with similar goals.

We use English data from XL-Sum and Wikilingua for English fine-tuning step while experimenting with respective dataset. MLQA, TyDiQA and XQuAD do not have any English training data. Following the trend (Lewis et al., 2020b; Clark et al., 2020) we use SQuAD v1.1 training data at English fine-tuning step.

For each dataset, we grouped the languages into three fixed clusters as per Table-1 and find the centroid language as described in Section-4.1. English is the high resource language and only used for supervised fine-tuning as described in section-4.2 so, it will not be part of any cluster. To make it more concrete, XQuAD dataset has 11 low-resource languages (excluding English), the centroid (Meta-training) languages are <tr,es,th> and non-centroid (Target) languages are <hi,ro,de,ar,vi,zh,ru,el>.

5.2 Baselines

Due to unavailability of prior zero-shot results for considered datasets, we design strong baselines based on recent model architectures.

- **EnZmT5**: Inspired from Maurya et al. (2021), we further train mT5 model with monolingual dataset in all 30 languages followed by task-specific English fine-tuning (similar to first three steps of Meta-XNLG model proposed in section 4.2). Then it is directly evaluated on the target languages in zero-shot setting.

- **FTZmT5**: In this model we fine-tune EnZmT5 baseline on all centroid languages. This will ascertain that the improvement of Meta-XNLG is not due to simply training on more datasets in different languages. This is close to the Lewis et al. (2020a)’s model but they use different dataset.

While training EnZmT5 and FTZmT5, we use all applicable precautions as suggested in sections 4.3 and grid search to find best hyper-parameters. We could not compare ZmBART performance with Meta-XNLG as authors did not use officially released evaluation datasets.

5.3 Evaluation Metrics

Both automatic and manual evaluation metrics are used to ensure the quality of the generated text. Particularly, for automatic evaluation ROUGE-L (Lin, 2004) and BLEU6 (Papineni et al., 2002) metrics are used for ATS and QG respectively. Similar to Chi et al. (2020b) we used three manual evaluation metrics: Fluency referring to how fluent the generated text is, Relatedness indicating the degree of the input’s context in the generated text and Correctness measuring the grammar and semantics of generated text. It is often observed that NLG systems suffer from the problem of Hallucination (Nie et al., 2019); the Relatedness metric provides clarity in such situations. The Correctness metric is hard metric which considers both semantic and grammatical aspects of generated text.

We randomly sampled 50 generated examples for each <task, dataset, language> triplet based on

\[ \text{BLEU-4 from modified } \text{Papineni et al., 2002} \text{ metrics used for ATS and QG respectively. Similar to } \text{Chi et al., 2020b} \text{ we used three manual evaluation metrics: Fluency referring to how fluent the generated text is, Relatedness indicating the degree of the input’s context in the generated text and Correctness measuring the grammar and semantics of generated text. It is often observed that NLG systems suffer from the problem of Hallucination (Nie et al., 2019); the Relatedness metric provides clarity in such situations. The Correctness metric is hard metric which considers both semantic and grammatical aspects of generated text. We randomly sampled 50 generated examples for each <task, dataset, language> triplet based on } \]

\[ \text{NLG is not mix BLEU-4 from modified } \text{sacreBLEU implementation, see appendix-A} \]
qualified and available native language experts in Hindi, Telugu, Tamil and Bengali languages. In total, we selected six triplets for evaluation. To ensure the quality, each selected triplet is evaluated by two sets of annotators. We asked each annotator to rate the generated text on a scale of 1-5 (where 1 is very bad and 5 is very good) for the metrics mentioned above. We anonymously shared the generated text from two baselines and Meta-X\textsubscript{NLG} to avoid any biased evaluation.

5.4 Implementation Details

We implemented Meta-X\textsubscript{NLG} using higher library\textsuperscript{7}. SGD with learning rate ($\alpha$) $1e^{-4}$ is used as inner-loop optimizer and AdamW with learning rate ($\beta$) $1e^{-5}$ is used as outer-loop optimizer. The inner iteration ($m$) value is 2 and meta-training batch size is 8. To partition the training batch into support set ($S$) and query set ($Q$), we experimented ($S$:$Q$) with [8:2, 7:3, 6:4, 5:5, 4:6] splits. The best results are obtained with equal partition, i.e., 5:5. We also experimented with [2, 5, 10, 15, 20, 25] training epochs. The best performance was observed at $10^{th}$ epoch. We use a standard mT5-small sequence-to-sequence Transformer architecture with 12 layers (each 16 heads). It has 1024 dimensions and approx 582M parameters. Additional layer-normalization with weight decay (0.1) was used with both the encoder and decoder. For input, the max sequence length is fixed to 512. We trained all the models on 1 Nvidia V100 GPU (32GB). Cross-entropy label smoothing is used as loss function. We use beam-search with beam size 4; max generation length is 100 for ATS (32 for QG) and min length is 1. To ensure the stated improvement on the MLQA dataset, we compute average BLEU scores across the best 5 checkpoints. We are unable to repeat such experiments for other datasets due to computational limits.

6 Results and Analysis

Automated evaluation results are shown in Table 3-6. Meta-X\textsubscript{NLG} consistently outperformed other two baselines on all five datasets and most of the languages. For the summarization task, among the 33 experiments (19 languages for XL-Sum and 14 for Wikilingua) Meta-X\textsubscript{NLG} gives best performance for 30 experiments. Wherever it loses out, it does so by small margin. We see that the performance gains for the Wikilingua are relatively smaller. This might be due to the nature of the Wikilingua dataset, we observe that the input documents are set of usage instructions for softwares/tools. For such data, many instructions need to be retained in the summary. This poses a challenge to all the models including Meta-X\textsubscript{NLG}. Similar observations are made by Maurya et al. (2021).

For the question generation task, Meta-X\textsubscript{NLG} achieves better performance than others except for one experiment - Indonesian language for TyDiQA. For MLQA, improvements achieved by the proposed model are marginal (see Table-6). Upon close inspection, we notice that MLQA had small number of languages, and the centroid languages are very distinct, i.e. they have higher mean distance to other languages from same cluster as compared to the other datasets (see Table-11). This might be a possible reason for such performance.

The human evaluation scores for all the three metrics are shown in Table-7. The human evaluations (across both annotator sets) correlate with automatic evaluations. Similar to the automatic evaluation, Meta-X\textsubscript{NLG} consistently outperformed both baselines for selected languages, tasks and datasets. High Fluency and Relatedness scores for Meta-X\textsubscript{NLG} indicates that most of generated text are fluent and not hallucinated respectively. The correctness metric considers both semantic and grammatical aspects; good scores on this metric indicate the acceptable performance for the proposed model in zero-shot setting. In QG, generating well-formed interrogative sentences is challenging, particularly in zero-shot setting due to unseen interrogative syntax structure of target language (Mitra et al., 2021; Maurya et al., 2021). The above-average fluency and correctness score for Meta-X\textsubscript{NLG} indicates that the model quickly adapts such syntax and performs better.

The consistent improvement in Meta-X\textsubscript{NLG} for most the typologically diverse target languages provides evidence that supervision transfer is more uniform. Considering decent automatic and manual evaluation scores in the zero-shot setting, we conclude that our model performs reasonably well except small performance gain with the MLQA dataset. Meta-X\textsubscript{NLG} is a zero-shot framework, and we do not assume any prior training/knowledge for new unseen LRL. The only constraints are: the new language should be part of base pre-trained models (mT5) and adaptive unsupervised pre-training

\textsuperscript{7}https://github.com/facebookresearch/higher
Table 2: Zero-shot Rouge-L scores for 19 target languages on XL-Sum dataset (Hasan et al., 2021). EnZmT5 (Maurya et al., 2021) and FTZmT5 are baseline models. Scores are reported after extensive hyper-parameter search for all the models.

| Model           | fr | gu | id | th | ta | hi | mu | ja | ko | tr | ru | sw | pt | ar | te | ar | uc | bn | zh |
|-----------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| EnZmT5          | 18.45 | 13.21 | 19.77 | 21.53 | 15.58 | 22.24 | 11.89 | 22.81 | 18.74 | 17.72 | 15.27 | 20.91 | 18.92 | 20.84 | 10.77 | 21.61 | 16.24 | 18.12 | 21.07 |
| FTZmT5          | 21.83 | 7.99 | 19.27 | 24.68 | 10.89 | 11.92 | 8.94 | 23.32 | 16.82 | 14.99 | 12.90 | 21.01 | 20.07 | 15.85 | 9.14 | 13.05 | 11.06 | 12.66 | 15.20 |
| Meta-XNLG       | 22.83 | 14.02 | 21.54 | 24.64 | 12.80 | 23.09 | 12.58 | 25.33 | 20.12 | 18.65 | 17.31 | 22.63 | 20.24 | 20.11 | 12.97 | 23.41 | 15.45 | 17.96 | 22.95 |

Table 3: Zero-shot Rouge-L scores for 14 target languages on Wikilingua dataset (Ladhak et al., 2020).

| Model           | id | fr | ar | pt | it | th | ru | cs | nl | de | ja | hi | el | ru | hi | tr |
|-----------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| EnZmT5          | 15.34 | 18.72 | 15.70 | 17.21 | 15.05 | 26.66 | 14.67 | 9.42 | 17.97 | 13.69 | 22.32 | 20.12 | 18.88 | 11.27 |
| FTZmT5          | 13.69 | 19.37 | 12.66 | 17.80 | 15.54 | 23.72 | 11.95 | 10.20 | 16.74 | 12.22 | 22.81 | 18.64 | 17.32 | 13.84 |
| Meta-XNLG       | 16.85 | 20.26 | 15.66 | 18.36 | 16.03 | 27.71 | 14.89 | 11.76 | 19.09 | 14.11 | 22.83 | 22.45 | 19.60 | 15.23 |

Table 4: Zero-shot BLEU scores for 8 target languages on XQuAD dataset (Artetxe et al., 2020).

| Model           | fl | ru | id | sw | ko | bn | ta |
|-----------------|----|----|----|----|----|----|----|
| EnZmT5          | 7.81 | 5.52 | 5.75 | 4.48 | 8.39 | 5.77 | 3.08 |
| FTZmT5          | 8.39 | 7.28 | 11.42 | 5.51 | 10.05 | 7.96 | 2.022 |
| Meta-XNLG       | 9.08 | 7.47 | 9.36 | 6.42 | 12.67 | 9.17 | 9.76 |

Table 5: Zero-shot BLEU scores on TyDiQA data.

| Model           | hi | es | ar | zh |
|-----------------|----|----|----|----|
| EnZmT5          | 3.06 | 6.94 | 3.46 | 13.70 |
| FTZmT5          | 5.14 | 6.16 | 2.21 | 13.38 |
| Meta-XNLG       | 5.66 | 7.03 | 3.66 | 15.13 |

Table 6: Zero-shot BLEU scores on MLQA data.

| Model           | Task/Data/Lang | Flu | Rel | Corr |
|-----------------|-----------------|-----|-----|------|
| Annotation set-1|                 |     |     |      |
| EnZmT5          | ATS/XL-Sum/bn   | 4.06 | 3.58 | 2.84 |
| FTZmT5          | ATS/XL-Sum/te   | 2.82 | 3.18 | 2.08 |
| Meta-XNLG       | ATS/XL-Sum/bn   | 4.12 | 4.34 | 3.44 |
| Annotation set-2|                 |     |     |      |
| EnZmT5          | ATS/XL-Sum/bn   | 3.70 | 3.23 | 3.26 |
| FTZmT5          | ATS/XL-Sum/te   | 2.62 | 2.48 | 2.16 |
| Meta-XNLG       | ATS/XL-Sum/bn   | 3.97 | 3.48 | 3.28 |

Table 7: Human Evaluation results for four languages (hi: Hindi, te: Telugu, ta: Tamil and bn: Bengali), two annotator sets, two tasks (ATS and QG) and all five datasets. Flu: Fluency, Rel: Relatedness and Corr: Correctness metrics. Results are shown for two annotation sets which ensure biased free evaluation. Reported scores are average of all the annotators in a annotator set.
(uses task-agnostic monolingual data only). Hence, adding new languages in Meta-X_{NLG} is a simple extension exercise.

### 6.1 Cross-lingual Transfer:

To have a more general view of the model’s learning of multiple languages, we perform similarity analysis among representations of the language tags (contextual representation of the $<f_{xx}> <2_{xx} >$ tokens from the beginning of the input in language $xx$). 10 languages are randomly selected from XL-Sum dataset. Each language input is passed through the encoder part of the models (EnZmT5 and Meta-X_{NLG}) and language tag representations (LTRs) are extracted. Cosine distance among LTRs is shown in figure-2. Baseline EnZmT5 has a high cosine distance between language tags obtained from three clusters. The performance gets distracted with many centroid languages. Another example is Turkish and Hindi languages share same cluster, in row 5 we did not include Turkish as centroid language which obtains poor performance on Hindi. Similar observations can be made for row 6. Overall, Meta-X_{NLG} trained with three centroid languages (row 14) performs best on most of the languages and on average. We conducted more extensive ablation study with XL-Sum dataset (see Table-13 in Appendix) and similar trends are observed.

### 6.2 Effect of Training Languages:

Table-8 shows the results with different language combinations for Meta-X_{NLG} training on XQuAD dataset. For this dataset, the centroid languages are Turkish (tr), Spanish (es) and Thai (th). Results are generally good when centroid languages are in the training set. Best results are obtained using three centroid languages from three clusters. The performance dropped when we included more centroid languages (rows 12-15). As discussed in section-4.1, learning gets distracted with many centroid languages.

We now try to have a closer look at the numbers. While training with non-centroid languages (rows 4, 8, 9), the model performs poorly, which validates the importance of centroid languages. Another example is Turkish and Hindi languages share same cluster, in row 5 we did not include Turkish as centroid

| Setup | XTrain-Lang | ar | be | ca | de | el | es | fi | fr | gu | hi | th | tr | ru | avg |
|-------|-------------|----|----|----|----|----|----|----|----|----|----|----|----|----|-----|
| 1     | fr           | 16.14 | 13.28 | 12.32 | 11.85 | 11.71 | 11.76 | 11.75 | 11.74 | 11.73 | 11.68 | 11.63 | 11.62 | 11.58 | 11.56 |
| 2     | en           | 14.89 | 11.44 | 11.44 | 11.34 | 11.28 | 11.28 | 11.28 | 11.28 | 11.28 | 11.28 | 11.28 | 11.28 | 11.28 | 11.28 |
| 3     | fr           | 17.25 | 13.34 | 13.34 | 13.34 | 13.34 | 13.34 | 13.34 | 13.34 | 13.34 | 13.34 | 13.34 | 13.34 | 13.34 | 13.34 |
| 4     | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 5     | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 6     | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 7     | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 8     | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 9     | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 10    | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 11    | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 12    | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 13    | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 14    | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 15    | fr           | 17.01 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |
| 16    | Meta-X_{NLG} | 17.00 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 | 13.02 |

Table 8: Meta-X_{NLG} zero-shot results on different training languages combinations of the XQuAD dataset. *x* indicates the language used in training, so scores are not zero-shot and not included.

### 7 Conclusion

In this work, we propose a novel Meta-X_{NLG} framework based on meta-learning and language clustering for effective cross-lingual transfer and generation. This is the first study that uses meta-learning for zero-shot cross-lingual transfer and generation. The evaluations are done on two challenging tasks (ATS and QG), five publicly available datasets and 30 languages. Consistent improvement for both human and automatic evaluation metrics is observed over baselines. The cross-lingual transfer analysis indicates the model’s ability towards uniform cross-lingual transfer across multiple low-resource languages. We will extend this study to more cross-lingual tasks and languages in the future.

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Appendices

A Evaluation Metric Setting

We use the multilingual version of ROUGE released by Hasan et al. (2021) where they use language-specific tokenizers and stemmers. Inspired by this, we also added the language-specific tokenizer in sacreBLEU implementation to compute BLEU Score.

B Miscellaneous

1. To the best of our knowledge, this is the first study towards meta-learning for the cross-lingual generation. The recent publications of applied meta-learning in NLP are listed here: https://jeffeuxmartin.github.io/meta-learning-hlp/ and https://github.com/ha-lins/MetaLearning4NLP-Papers (accessed on 15th March, 2022)

2. In the proposed framework the data instance tag is <fxx><2xx>, where <fxx> is tag for input document language and <2xx> for target language for example: <fen> <2en>. In this work, the input and target document languages are the same. The tag will be easily adapted in the future, where input and target document languages are different. For example, the tag <fen> <2fr> indicates that the input document language is English (en) and target document language is French (fr).

3. We are aware that, recently adapter modules (Houlsby et al., 2019) have emerged as alternate solution for catastrophic forgetting problem. In future, we will compare Meta-XNLG performance with Meta-XNLG + adapters model.

4. The additional Tamil language in TyDiQA is taken from Kaggle.

C Other Details

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https://www.kaggle.com/c/chaii-hindi-and-tamil-question-answering/data
Table 9: Details of the datasets used in Meta-XNLG. For adaptive pre-training small 5k/1k/1k dataset is used. *- English is a high resource language for which all three splits were used, as shown in Row 1. **-additional language added in the dataset. ***-dataset does not have validation split, so a test data set of centroid languages is used in training. ****-TyDiQA does not have a test set, so the training set is used for evaluation (test set).

| SN | Language | ISO-2 | ISO-3 | Adap. PT train/valid/test | XL-Sum test | Wikilingua test | MLQA*** test | TyDiQA**** test | XQuAD*** test |
|----|----------|-------|-------|---------------------------|-------------|----------------|--------------|----------------|--------------|
| 1  | English* | en     | eng   | 5k/1k/1k                  | 300k/10k/1k | 100k/13k/28k  | 90k/100k/11k | 90k/100k/11k  | 90k/100k/11k |
| 2  | Hindi    | hi     | hin   | 5k/1k/1k                  | 8847        | 1983          | 4918         | -              | -            |
| 3  | Urdu     | ur     | urd   | 5k/1k/1k                  | 8458        | -             | -            | -              | -            |
| 4  | Telugu   | te     | tel   | 5k/1k/1k                  | 1302        | 899           | -            | -              | 5563         |
| 5  | Turkish  | tr     | tru   | 5k/1k/1k                  | 3397        | -             | -            | -              | -            |
| 6  | Finnish  | fi     | fin   | 5k/1k/1k                  | -           | -             | 6855         | -              | -            |
| 7  | Japanese | ja     | jpn   | 5k/1k/1k                  | 889         | 2529          | 5000**       | -              | -            |
| 8  | Korean   | ko     | kor   | 5k/1k/1k                  | 550         | 2435          | -            | 1620          | -            |
| 9  | Gujarati | gu     | guj   | 5k/1k/1k                  | 1139        | -             | -            | -              | -            |
| 10 | Bengali  | bn     | ben   | 5k/1k/1k                  | 1012        | -             | 2390         | -              | -            |
| 11 | Marathi  | mr     | mar   | 5k/1k/1k                  | 1362        | -             | -            | -              | -            |
| 12 | Nepali   | np     | nep   | 5k/1k/1k                  | 725         | -             | -            | -              | -            |
| 13 | Tamil    | ta     | tam   | 5k/1k/1k                  | 2027        | -             | 368**        | -              | -            |
| 14 | Punjabi  | pa     | pan   | 5k/1k/1k                  | 1026        | -             | -            | -              | -            |
| 15 | Swahili  | sw     | swa   | 5k/1k/1k                  | 987         | -             | 2755         | -              | -            |
| 16 | Spanish  | es     | spa   | 5k/1k/1k                  | 4763        | 22626         | 5523         | -              | 1190         |
| 17 | Italian  | it     | ita   | 5k/1k/1k                  | -           | 10187         | -            | -              | -            |
| 18 | Portuguese | pt | por   | 5k/1k/1k                  | 7175        | 16326         | -            | -              | -            |
| 19 | Romanian | ro     | ron   | 5k/1k/1k                  | -           | -             | -            | 1190**        | -            |
| 20 | Dutch    | nl     | nld   | 5k/1k/1k                  | -           | 6248          | -            | -              | -            |
| 21 | German   | de     | deu   | 5k/1k/1k                  | -           | 11667         | 4517         | -              | 1190         |
| 22 | French   | fr     | fra   | 5k/1k/1k                  | 1086        | 12728         | -            | -              | -            |
| 23 | Russian  | ru     | rus   | 5k/1k/1k                  | 7780        | 10377         | -            | 6490          | 1190         |
| 24 | Czech    | cs     | ces   | 5k/1k/1k                  | 1438        | -             | -            | -              | -            |
| 25 | Vietnamese | vi | vie   | 5k/1k/1k                  | 4013        | 3916          | 5459         | -              | 1190         |
| 26 | Thai     | th     | tha   | 5k/1k/1k                  | 826         | 2949          | -            | -              | 1190         |
| 27 | Chinese (Sim) | zh | zho   | 5k/1k/1k                  | 4670        | 3772          | 5137         | -              | 1190         |
| 28 | Indonesian | id | ind   | 5k/1k/1k                  | 4780        | 9495          | -            | 5702          | -            |
| 29 | Greek    | el     | ell   | 5k/1k/1k                  | -           | -             | -            | -              | 1190         |
| 30 | Arabic   | ar     | ara   | 5k/1k/1k                  | 4689        | 5840          | 5135         | 14805         | 1190         |

Table 10: Size of centroid languages validation set used in the proposed Meta-XNLG framework. The same number of examples are sampled from each centroid language.
Figure 3: Language clustering based on multi-view representation proposed by Oncevay et al. (2020). We intentionally show more than 30 languages in the clustering, which will be useful for scaling the proposed work in the future. As per our application need, we added multiple languages in clustering over originally proposed by the authors. Additional languages are: Telugu (tel), Gujarati (guj), Nepali (nep), Punjabi (pan), English (eng).

Table 11: Details of language clustering for each dataset, mean cosine distance (meanCD), and centroid languages. For each dataset, we group languages into three clusters as shown in Figure 1. The Swahili language does not have any typological or task-based representations, so we added it to cluster 1 based on language typological features and heuristics. For the TyDiQA dataset, only two clusters are obtained as cluster-2 does not have any language. If a cluster has only two languages, we randomly selected any language as centroid language.
Table 12: Results with different adaptive pre-training objectives. mT5 is a base pre-trained model for above all experimental setups. T5 PTObj is the T5 model’s pre-training objective proposed by Rafail et al. (2020). EngFT is English fine-tuning of base/adaptive pre-trained model. The results are shown on selected languages with XL-Sum dataset in standard supervised fine-tuning (English) and zero-shot setting (Hindi and Bengali). Proposed adaptive pre-training outperforms existing approaches for zero shot transfer.

| Setup | MetrEval Language | tr | ga | ru | bn | pt | vi | de | fr | mr | tr | ja | ne | ko | zh | ar | el | zh-hans | zh-hant | zh | zh-tw | zh-sg | zh-cn | zh-hk | zh-tw | zh-sg | zh-cn | zh-hk | zh-tw | zh-sg | zh-cn | zh-hk | zh-tw | zh-sg | zh-cn | zh-hk | zh-tw | zh-sg | zh-cn | zh-hk | zh-tw | zh-sg | zh-cn | zh-hk | zh-tw | zh-sg | zh-cn | zh-hk | zh-tw | zh-sg | zh-cn | zh-hk | zh-tw | zh-sg | zh-cn | zh-hk |
|-------|-------------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|---------|---------|----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| R-L   | English (Supervised) | Hindi (Zero-shot) | Bengali (Zero-shot) | R-L   | English (Supervised) | Hindi (Zero-shot) | Bengali (Zero-shot) |
|-------|-------------------|-------------------|-------------------|-------|-------------------|-------------------|-------------------|
| joint training (T5 PTObj + EngFT [1:100]) (Xue et al., 2021) | 34.19 12.09 26.47 | 22.02 06.03 18.60 | 13.76 03.64 12.32 |
| random BM25 Objective followed by EngFT (Maurizi et al., 2021) | 33.38 11.57 26.00 | 24.31 07.11 19.91 | 16.23 04.32 14.66 |
| T5 PTObj followed by EngFT (proposed) | 34.15 11.99 26.59 | 26.75 08.59 22.24 | 18.63 05.71 16.12 |

Table 13: Meta-XNLG’s zero-shot evaluation scores (Rouge-L) with different meta-training language combinations on the XL-Sum dataset. We cut the hierarchical clustering dendrogram shown in Figure 3, at the lower level to obtain more clusters. In total, we obtain eight centroid languages, i.e., pa, es, vi, tr, ja, mr and fr and ru. '-' indicates the language used in training, so scores are not zero-shot and not included. Markers "*", "**", and "***" indicate meta training with all-centroid, all-non-centroid, and mix of both (centroid & non-centroid) languages.
Figure 4: Zero-shot samples generated by Meta-XNLG in Telugu, Tamil, Bengali and Hindi languages. The top three samples are for ATS and the bottom three are for QG tasks. The generated samples are taken from all five datasets. In some instances, the model learns to generate an actual target language script even if the reference is in transiterterated form. See the underlined token (in red font color) in the TyDiQA-Tamil example. 