Meta-X_{NLG}: 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-X_{NLG}) 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. The careful design of the model makes this end-to-end NLG setup less vulnerable to the accidental translation problem, which is a prominent concern in zero-shot cross-lingual NLG tasks.

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/collecting 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 (X_{NLG})*. Particularly, we focus on zero-shot X_{NLG} for low-resource languages. Unlike NLU tasks, we observe that zero-shot NLG is a more

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

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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_{NLG}[2], 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_{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_{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). We make an attempt to bridge this gap via meta-learning.

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.

[2]code & pre-trained models: https://github.com/kaushal0494/Meta_XNLG

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 $p(\mathcal{D})$ over task datasets $\{\mathcal{D}_1, \mathcal{D}_2, \dots, \mathcal{D}_n\}$ where $\mathcal{D}_i$ is associated with i^{th} task $\mathcal{T}_i$. Each $\mathcal{D}_i$ has *support set* and *query set* $\mathcal{D}_i = \{\mathcal{S}_i, \mathcal{Q}_i\}$. *Support set* and *Query set* are analogous to train and test splits of the traditional machine learning. We use f_θ to denote a neural network model parameterized by θ.

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

$$\theta^* = \arg\min_\theta \sum_{D_i \sim p(D)} \mathcal{L}_i(f_{\theta_i^{(m)}}) \tag{1}$$

where $\mathcal{L}_i(f_{\theta_i^{(m)}})$ is the loss obtained on query set for task $\mathcal{T}_i$ and $f_{\theta_i^{(m)}}$ is obtained after m iteration of SGD update with Task $\mathcal{T}_i$ as:

$$f_{\theta_i^{(m)}} = f_\theta - \alpha \nabla_\theta \mathcal{L}_i(f_\theta)$$

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

$$\theta = \theta - \beta \nabla_\theta \sum_{D_i \sim p(D)} \mathcal{L}_i(f_{\theta_i^{(m)}}) \tag{2}$$

Where α is inner-loop learning rate and β is meta (outer-loop) learning rate. In the adaptation phase, the model is initialized with with learned optimal meta-parameters θ^*, 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-X$_{\text{NLG}}$ 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, Oncevay 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 $C = \{L_1, L_2, \dots L_t\}$, where each L_i is multi-view representation of i^{th} language, the centroid language $L^* \in C$ is defined as:

$$L^* = \arg\min_{L_i \in C} \sum_{L_j \in C} d(L_j, L_i). \tag{3}$$

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

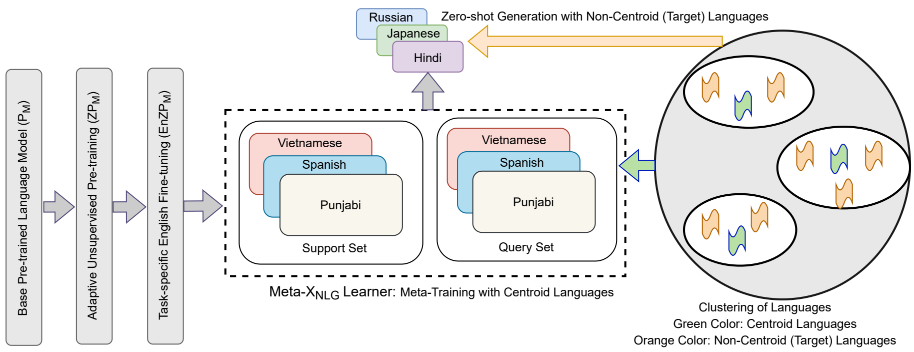


Figure 1: An overview of Meta-X_{NLG} framework

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-X_{NLG} 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 θ_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_{θ^*} 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

Cluster-1(14)	Cluster-2(8)	Cluster-3(8)
hi,ur,te,tr,ja,fi,ko,gu, bn,mr,np,ta,pa,sw	es,it,pt,ro, nl,de,en,fr	ru,cs,vi,th, zh,id,el,ar

Table 1: Clustering of considered 30 Languages

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 $EnZP_M$ (P) with parameters θ_P, meta-learner f_θ with parameter θ.
Require: α, β: step size hyper-parameters

```
Initialize θ ← θ_P
while not done do
    Sample batch of tasks T = T_1, T_2, ... T_b ∼ p(D)
    for all T_i in T do
        Initialize θ_i ← θ
        Split D_i to form support set S_i and query set Q_i
        for all inner_iter steps m do
            Compute ∇_{θ_i^(m)} L_{T_i}^{S_i}(P_{θ_i^(m)})
            Do SGD: θ_i^{m+1} = θ_i^m − α∇_{θ_i^(m)} L_{T_i}^{S_i}(P_{θ_i^(m)})
        end for
        MetaUpdate: θ = θ − β∇_θ Σ_{j=1}^{b} L_{T_i}^{Q_i}(P_{θ_i^(m)})
    end for
end while
Do zero-shot/few-shot learning with meta-learner f_{θ*} where θ* 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-X$_{\text{NLG}}$ framework.

- *Adding Language Tag:* We concatenate <*fxx*> <*2xx*> 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-X$_{\text{NLG}}$'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/

correct questions that can produce the answer. We use three publicly available multilingual question and answering (QA) datasets: MLQA (Lewis et al., 2020b), TyDiQA (Clark et al., 2020) and XQuAD (Artetxe et al., 2020). Each instance is triplet of <passage, question, answer>. We concatenated *answer* and *passage* with delimiter </s> in same order as input for models.

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 crowd-source questions on English and translate into target languages by professional translators. As our frame-work 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 languages has 1190 question-answer pairs. SQuAD is popular question answering dataset consisting of around 100k <passage, question, answer> triplets. We added additional Japanese language data set (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>[4].

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-X_{NLG} 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-X_{NLG} 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-X_{NLG} as authors did not use officially released evaluation datasets[5].

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 **BLEU**[6] (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

[4]see Table-11 for language distribution to the cluster for each dataset and Table-9 for datasets statistics

[5]for Wikilingua dataset, official splits are released recently.

[6]reported scores are `case − mix` BLEU-4 from modified 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_{XNLG} to avoid any biased evaluation.

5.4 Implementation Details

We implemented Meta-X_{NLG} using *higher* library[7]. SGD with learning rate (α) $1e-4$ is used as inner-loop optimizer and AdamW with learning rate (β) $1e-5$ 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_{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_{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_{NLG}. Similar observations are made by Maurya et al. (2021).

For the question generation task, Meta-X_{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_{NLG} consistently outperformed both baselines for selected languages, tasks and datasets. High *Fluency* and *Relatedness* scores for Meta-X_{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_{NLG} indicates that the model quickly adapts such syntax and performs better.

The consistent improvement in Meta-X_{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_{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

[7] https://github.com/facebookresearch/higher

Model	**fr**	**gu**	**id**	**th**	**ta**	**hi**	**mr**	**ja**	**ko**	**tr**	**ru**	**sw**	**pt**	**ar**	**te**	**ur**	**ne**	**bn**	**zh**
EnZmT5	18.45	13.21	19.77	21.53	11.58	22.24	11.89	22.81	18.74	17.72	15.27	18.91	18.92	18.44	10.77	21.61	**16.24**	16.12	21.07
FTZmT5	21.83	7.98	19.27	**24.68**	10.80	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-X_{NLG}	**22.83**	**14.02**	**21.54**	24.61	**12.88**	**23.09**	**12.58**	**25.33**	**20.12**	**18.65**	**17.31**	**22.63**	**20.24**	**20.11**	**12.07**	**23.41**	15.45	**17.96**	**22.95**

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	**id**	**fr**	**ar**	**pt**	**it**	**th**	**ru**	**cs**	**nl**	**de**	**ja**	**zh**	**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	14.45
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-X_{NLG}	**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 3: Zero-shot *Rouge-L* scores for 14 target languages on Wikilingua dataset (Ladhak et al., 2020).

Model	**ar**	**de**	**zh**	**vi**	**hi**	**el**	**ru**	**ro**
EnZmT5	8.55	9.99	23.76	17.29	9.55	8.18	10.98	11.27
FTZmT5	5.82	9.040	22.87	16.47	9.05	6.95	8.87	10.31
Meta-X_{NLG}	**8.63**	**10.52**	**24.89**	**20.92**	**11.90**	**9.01**	**11.41**	**12.24**

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

Model	**fi**	**ru**	**id**	**sw**	**ko**	**bn**	**ta**
EnZmT5	7.87	5.52	5.75	4.48	8.59	5.77	3.08
FTZmT5	8.39	7.28	**11.42**	5.51	10.05	7.96	2.022
Meta-X_{NLG}	**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	5.06	6.94	3.46	13.70
FTZmT5	5.14	6.16	2.21	13.38
Meta-X_{NLG}	**5.66**	**7.03**	**3.66**	**15.13**

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

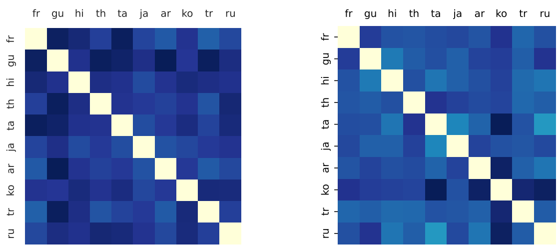
Model	**Task/Data/Lang**	**Flu**	**Rel**	**Corr**	**Task/Data/Lang**	**Flu**	**Rel**	**Corr**
Annotator set-1								
EnZmT5	ATS/XL-Sum/bn	4.06	3.58	2.84	ATS/XL-Sum/te	4.28	3.94	3.70
FTZmT5		2.82	3.18	2.08		3.46	3.46	3.22
Meta-X_{NLG}		**4.12**	**4.34**	**3.44**		**4.50**	**4.22**	**4.04**
Annotator set-2								
EnZmT5	ATS/XL-Sum/bn	3.70	3.23	3.26	ATS/XL-Sum/te	3.56	3.50	3.20
FTZmT5		2.62	2.48	2.16		3.02	2.84	2.60
Meta-X_{NLG}		**3.97**	**3.48**	**3.28**		**4.18**	**4.10**	**3.88**
Annotator set-1								
EnZmT5	ATS/Wiki/hi	4.00	3.72	3.68	QG/XQuAD/hi	4.12	4.24	2.54
FTZmT5		4.07	3.39	3.83		4.22	4.02	2.56
Meta-X_{NLG}		**4.09**	**3.80**	**3.97**		**4.42**	**4.34**	**2.86**
Annotator set-2								
EnZmT5	ATS/Wiki/hi	4.38	4.22	4.00	QG/XQuAD/hi	3.28	3.63	2.82
FTZmT5		4.57	**4.44**	4.08		3.24	3.34	2.89
Meta-X_{NLG}		**4.66**	**4.44**	**4.16**		**3.59**	**3.67**	**3.24**
Annotator set-1								
EnZmT5	QG/MLQA/hi	3.48	3.70	3.46	QG/TyDiQA/ta	4.25	4.06	3.10
FTZmT5		3.44	3.42	3.18		3.25	3.01	2.07
Meta-X_{NLG}		**3.70**	**3.74**	**3.56**		**4.74**	**4.20**	**3.39**
Annotator set-2								
EnZmT5	QG/MLQA/hi	**3.30**	3.28	2.40	QG/TyDiQA/ta	3.00	4.08	2.82
FTZmT5		3.10	3.44	2.84		2.55	3.045	1.83
Meta-X_{NLG}		3.24	**3.70**	**2.88**		**4.04**	**4.46**	**3.20**

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 <*fxx*> <*2xx*> 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 LTRs and the shared latent representation space is not much aligned. Meta-X_{NLG} has lower distances and shared latent representation space is more aligned across languages.



(a) Baseline (b) Meta-X_{NLG}

Figure 2: Cosine distance between language tags obtained from EnZmT5 and Meta-X_{NLG} for 10 langues from XL-Sum dataset. Dark color indicate higher cosine distance.

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 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.

SetUp	MTrain Lang	ar	de	zh	vi	hi	el	ru	ro	avg
1	tr	6.14	8.61	23.67	19.81	**10.91**	6.80	9.53	10.17	11.89
2	es	6.68	10.82	20.89	16.84	7.96	7.79	10.02	13.28	11.78
3	th	5.43	8.47	23.10	17.46	7.99	6.85	9.41	8.98	11.08
4	ro	4.78	9.49	19.80	15.75	6.01	-	8.25	9.90	10.56
5	es,th	6.07	10.30	18.74	16.10	7.74	7.14	9.56	12.37	11.00
6	tr,th	6.02	8.58	25.05	19.08	10.38	6.64	9.27	10.40	11.92
7	ro,de	5.53	-	22.69	15.37	7.59	6.37	8.85	-	11.06
8	zh,ar	-	8.92	-	15.55	8.22	6.58	9.72	10.49	9.91
9	de,ru	6.02	-	17.68	12.40	8.05	7.32	-	12.56	10.67
10	vi,th, el	6.15	9.86	23.26	-	8.86	-	9.94	11.71	11.63
11	de,tr,el	5.91	-	14.29	18.15	9.50	-	9.88	12.28	11.66
12	tr,es,th, ru	6.03	**11.88**	23.13	19.56	9.58	7.04	-	**13.62**	12.97
13	tr,es,th,de	6.34	-	17.25	19.47	8.91	7.73	9.95	13.14	11.82
14	tr,es,th,de,ru	6.45	-	**25.14**	16.31	9.51	6.72	-	12.39	12.75
15	tr,es,th,de,ru,ar	-	-	22.58	15.65	8.04	6.74	-	11.81	12.96
16	Meta-X_{NLG}	**8.63**	10.52	24.89	**20.92**	**11.90**	**9.01**	**11.41**	12.24	**13.69**

Table 8: Meta-X_{NLG} zero-shot results on different training languages combinations of the XQuAD dataset. '-' 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-X_{NLG} performance with Meta-X_{NLG} + adapters model.

4. The additional Tamil language in TyDiQA is taken from Kaggle[8]

C Other Details

[8] `https://www.kaggle.com/c/chaii-hindi-and-tamil-question-answering/data`

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/11k/11k	100k/13k/28k	90k/10k/11k	90k/10k/11k	90k/10k/11k
2	Hindi	hi	hin	5k/1k/1k	8847	1983	4918	-	1190
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	-	-	-	1190
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	5253	-	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	10577	-	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	5335	14805	1190

Table 9: Details of the datasets used in Meta-X_{NLG}. 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).

Dataset	1st Centroid Lang		2nd Centroid Lang		3rd Centroid Lang	
	Lang	Val Size	Lang	Val Size	Lang	Val Size
XL-Sum	Punjabi	1026	Spanish	1026	Vietnamese	1026
Wikilingua	Korean	1011	Spanish	1011	Vietnamese	1011
MLQA	Japanese	4517	German	4517	Vietnamese	4517
TyDiQA	Telugu	5562	-	-	Arabic	5562
XQuAD	Turkish	1190	Spanish	1190	Thai	1190

Table 10: Size of centroid languages validation set used in the proposed Meta-X_{NLG} framework. The same number of examples are sampled from each centroid language.

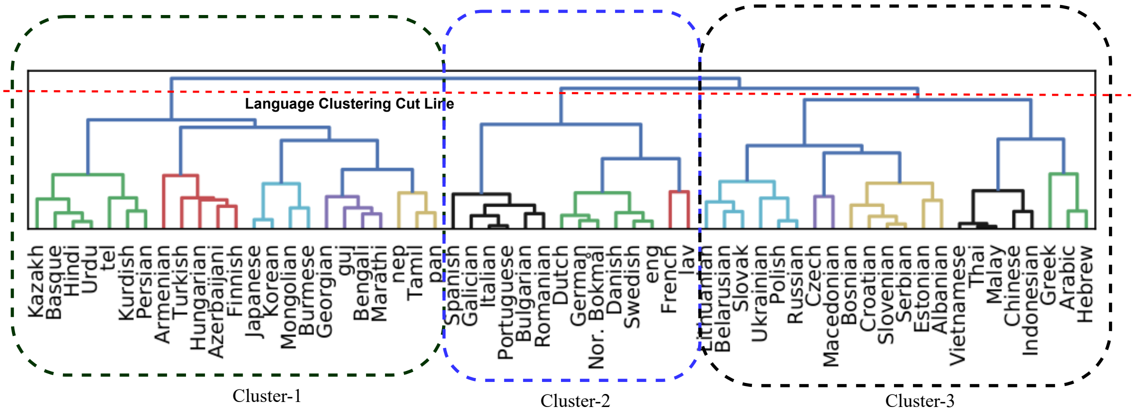

Figure 3: Language clustering based on multi-view representation proposed by Oncevay et al. (2020). We intentionally show more than 30 languages in the clustering, which will be useful for scaling the proposed work in the future. As per our application need, we added multiple languages in clustering over originally proposed by the authors. Additional languages are: Telugu (tel), Gujarati (guj), Nepali (nep), Punjabi (pan), English (eng).

Task/Dataset	Cluster-1		Cluster-2		Cluster-3		Centroid Lang	Non-Centroid Lang
	Lang	MeanCD	Lang	MeanCD	Lang	MeanCD	Meta-train Lang	Target Lang
Sum/XL-Sum	Punjabi	0.505	Spanish	0.253	Vietnamese	0.291	Punjabi	Tamil ,Marathi
	Tamil	0.547	Portuguese	0.437	Thai	0.326	Spanish	Gujarati , Bengali
	Marathi	0.548	French	0.477	Indonesian	0.327	Vietnamese	Telugu, Hindi
	Gujarati	0.550			Arabic	0.465		Nepali , Urdu
	Bengali	0.566			Chinese	0.561		Japanese, Turkish
	Telugu	0.574			Russian	0.902		Korean, Swahili
	Hindi	0.630						Portuguese, French
	Nepali	0.659						Thai, Indonesian
	Urdu	0.663						Arabic, Chinese
	Japanese	0.749						Russian
	Turkish	0.803						
	Korean	0.808						
	Swahili	-						
Sum/Wikilingua	Korean	0.558	Spanish	0.459	Vietnamese	0.484	Korean	Japanese, Turkish
	Japanese	0.583	French	0.476	Thai	0.496	Spanish	Hindi, French
	Turkish	0.620	German	0.529	Indonesian	0.536	Vietnamese	German, Portuguese
	Hindi	1.166	Portuguese	0.535	Arabic	0.595		Italian, Dutch
			Italian	0.566	Chinese	0.758		Thai, Indonesian
			Dutch	0.674	Russian	0.897		Arabic, Chinese
					Czech	1.374		Russian, Czech
QG/MLQA	Japanese	1.156	German	0.843	Vietnamese	0.299	Japanese	Hindi, Spanish
	Hindi	1.156	Spanish	0.843	Chinese	0.459	German	Chinese, Arabic
					Arabic	0.483	Vietnamese	
QG/TyDiQA	Telugu	0.682			Arabic	0.579	Telugu	Tamil, Bengali
	Tamil	0.719			Indonesian	0.619	Arabic	Finnish, Korean
	Bengali	0.769			Russian	0.940		Swahili, Indonesian
	Finnish	0.785						Russian
	Korean	0.828						
	Swahili	-						
QG/XQuAD	Turkish	1.038	Spanish	0.606	Thai	0.515	Turkish	Hindi, Romanian
	Hindi	1.038	Romanian	0.788	Arabic	0.516	Spanish	German, Arabic
			German	1.024	Vietnamese	0.519	Thai	Vietnamese, Chinese
					Chinese	0.813		Russian, Greek
					Russian	0.926		
					Greek	1.071		

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.

Setup	English (Supervised)			Hindi (Zero-shot)			Bengali (Zero-shot)		
	R-1	R-2	R-L	R-1	R-2	R-L	R-1	R-2	R-L
Without Adaptive Pre-training Step	36.05	13.87	28.34	00.32	00.06	00.32	00.13	00.00	00.13
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
randSum Objective followed by EngFT (Maurya 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	08.39	22.24	18.63	05.71	16.12

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 Raffel 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	Meta-Train Langs	fr	gu	id	th	ta	hi	mr	ja	ko	tr	ru	sw	pt	ar	te	ur	ne	bn	zh	avg
1*	pa	16.59	7.55	15.87	23.57	11.10	13.22	9.54	24.17	17.67	15.61	13.51	17.34	16.42	15.94	9.19	12.69	11.84	13.25	20.71	15.04
2*	es	21.35	12.73	19.54	23.82	10.42	18.77	10.99	24.15	18.02	15.87	14.10	20.03	19.72	17.46	10.13	20.12	15.06	16.00	22.01	17.38
3*	vi	19.67	12.34	18.69	25.02	11.05	19.41	10.90	23.77	18.46	15.15	14.56	20.40	18.02	17.43	10.69	20.23	14.42	15.47	21.58	17.22
4*	ru	17.60	12.89	16.97	23.54	10.50	18.03	10.75	24.28	18.09	16.36	-	18.25	17.32	17.63	10.44	20.52	14.28	14.40	22.18	16.89
5*	tr	16.57	12.83	16.04	23.77	10.10	17.72	10.65	24.06	17.01	-	14.90	19.46	17.34	17.59	10.40	20.12	13.51	13.35	21.01	16.46
6**	np	16.89	9.23	16.47	23.44	10.70	21.51	10.45	24.73	17.12	15.28	14.16	17.03	16.54	16.03	10.43	19.21	-	13.28	21.81	16.35
7**	th	17.86	11.60	17.25	-	10.78	17.98	10.30	21.07	17.89	15.73	14.48	18.16	17.59	17.19	9.87	20.11	13.56	15.65	15.35	15.69
8*	vi, pa	19.50	7.98	18.02	24.41	11.25	13.33	9.45	23.96	17.37	15.09	13.61	19.34	17.99	16.13	9.11	14.05	11.93	13.20	18.91	15.51
8*	tr, es	21.40	12.55	19.73	23.75	11.65	20.61	10.71	24.92	19.28	-	14.12	20.11	19.44	17.17	11.74	21.40	14.78	16.54	22.82	17.93
10*	fr, vi	-	12.49	19.51	23.72	11.12	18.83	10.38	24.01	18.74	15.98	14.01	19.40	18.96	17.18	10.52	20.44	14.32	15.19	22.36	17.06
11**	ur, zh	18.06	12.56	17.26	22.30	11.95	14.27	11.53	21.40	18.51	17.02	14.73	17.58	17.20	17.76	11.18	-	14.41	15.98	-	16.10
12**	th, pt	21.28	12.39	19.60	-	10.83	17.90	10.04	22.49	17.02	16.07	14.52	20.19	-	17.61	10.00	19.79	13.77	15.10	21.45	16.47
13@	pa, pt	21.13	8.72	19.92	23.89	11.64	14.38	9.65	24.13	17.36	16.89	14.91	20.90	-	17.36	9.95	15.53	11.66	13.37	22.04	16.30
14@	es, bn	21.61	10.53	18.85	23.23	11.06	17.33	10.15	24.31	17.25	15.68	13.69	19.32	19.27	16.29	10.46	20.40	11.75	-	19.48	16.70
15*	pa,fr,ru	-	9.80	19.17	23.39	10.54	13.97	9.43	24.41	17.50	16.56	-	19.52	19.07	16.08	9.03	16.44	11.43	13.01	21.71	15.95
16*	pa,es,ru	21.34	9.42	19.04	24.58	10.67	13.17	9.02	24.04	16.92	16.30	-	19.90	19.60	16.20	8.98	14.97	11.86	12.76	21.89	16.15
17*	vi,pa,fr	-	9.75	19.31	23.65	11.18	13.98	9.41	24.52	17.91	15.88	13.79	20.20	19.24	16.28	9.47	15.68	11.78	13.75	19.48	15.85
18**	ko,pt,th	21.66	12.94	19.93	-	11.94	20.35	10.42	24.46	-	17.99	15.55	21.22	-	18.58	11.23	21.54	15.20	16.06	16.72	17.24
19**	gu,pt,ar	21.83	-	19.52	23.74	10.30	14.46	7.71	23.51	15.57	15.34	13.73	19.40	-	-	9.62	18.77	11.30	12.88	21.03	16.17
20@	es,th,ar	22.11	12.14	19.60	-	10.60	17.22	9.92	22.88	16.78	16.18	13.81	20.42	20.09	-	10.25	19.55	13.58	15.35	17.27	16.34
21@	pa,pt,vi	21.75	9.65	19.80	24.49	11.41	13.82	9.81	24.51	17.70	16.16	14.55	20.39	-	17.28	10.04	15.71	11.70	13.91	20.97	16.31
22*	pa,es,vi,fr	-	9.35	19.74	23.91	11.11	13.86	8.96	24.82	17.70	16.54	13.57	20.65	20.16	16.43	9.52	16.76	11.73	13.48	19.81	16.01
23*	pa,ep,vi,ru	21.90	8.39	19.28	**24.89**	10.65	14.19	9.38	24.25	16.47	16.00	-	21.20	20.12	16.38	9.19	16.07	11.62	12.98	19.03	16.06
24*	pa,es,vi, tr	22.35	9.89	20.57	24.59	11.45	15.10	9.59	25.44	17.70	-	13.89	21.55	20.28	17.23	10.00	17.20	12.73	13.58	19.82	16.83
25**	zh,bn,te,pt	21.73	10.94	18.98	22.99	10.58	16.23	9.46	20.57	16.16	15.80	13.57	20.23	-	16.23	-	19.51	12.23	-	-	16.35
26**	id,sw,ur,pt	22.70	12.77	-	24.17	10.95	15.94	10.68	24.77	17.58	17.13	14.42	-	-	18.64	10.39	-	13.70	14.40	22.87	16.74
27@	pa,es,vi,hi	21.81	8.66	19.21	24.43	10.64	-	11.03	24.25	17.20	16.12	12.89	20.86	19.93	16.25	9.58	16.15	**16.36**	12.56	13.78	16.21
28@	pa,es,vi,ko	22.33	12.47	20.70	23.70	12.53	19.55	10.75	25.44	-	17.90	15.02	**22.63**	19.97	18.33	11.68	21.52	14.71	16.26	21.32	18.16
29*	pa,es,vi,fr,tr	-	10.26	20.39	24.04	11.12	14.79	9.08	25.42	17.75	-	13.35	21.17	20.28	16.50	9.65	17.43	12.43	14.01	20.62	16.37
30*	pa,es,vi,ru,mr	21.77	10.12	19.44	23.85	10.81	23.85	-	24.20	16.95	16.02	-	20.60	19.97	16.30	9.57	17.46	15.71	13.47	18.40	17.56
31**	id,sw,ur,po,te	22.43	11.19	-	23.88	9.87	16.08	9.64	24.21	16.05	17.05	14.19	-	-	18.54	-	-	13.08	13.19	20.44	16.42
32@	pa,es,te,mr,gu	20.51	-	18.05	22.01	9.69	**23.94**	-	21.93	15.32	15.04	11.83	18.51	19.39	14.60	-	16.70	15.81	12.70	10.13	16.63
33*	pa,es,vi,fr,tr,ru	-	9.98	20.59	24.61	11.14	14.72	9.21	25.18	17.53	-	-	21.54	20.55	16.61	9.65	17.72	12.07	13.71	21.80	16.66
34*	pa,es,vi,fr,tr,ru,mr	-	10.15	20.65	24.42	10.56	24.34	-	24.66	17.09	-	-	21.28	20.60	16.11	9.97	18.21	15.81	13.21	19.32	17.76
35*	pa,es,vi,fr,tr,ru,mr,ja	-	9.88	19.61	23.51	9.83	23.40	-	-	13.27	-	-	21.43	**20.36**	15.83	9.24	15.66	16.24	12.68	20.32	16.52
36*	**Meta-X_{NLG}(pa,es,vi)**	**22.83**	**14.02**	**21.54**	24.61	**12.88**	23.09	**12.58**	25.33	**20.12**	**18.65**	**17.31**	**22.63**	20.24	**20.11**	**12.07**	**23.41**	15.45	**17.96**	**22.95**	**19.40**

Table 13: Meta-X_{NLG}'s zero-shot evaluation scores (Rouge-L) with different meta-training language combinations on the XL-Sum dataset. We cut the hierarchical clustering dendogram 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, 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.

Telugu-XLSum

Input Document: ప్రభుత్వంలో ఆర్టీసీ విలీనం సహా తమ డిమాండ్లన్నింటినీ సాధించే వరకూ పోరాటం ఆపబోమని కార్మికులు ప్రకటించారు. ఆర్టీసీ కార్మిక సంఘాల జేఏసీ ఆధ్వర్యంలో ఈ సభ జరిగింది. కార్మికులకు మద్దతుగా పలు రాజకీయ పార్టీల నాయకులు దీనికి హాజరయ్యారు. సభ జరిగిన సరూర్‌నగర్ ఇండోర్ స్టేడియం కార్మికులతో నిండిపోయింది. కాంగ్రెస్ నాయకుడు రేవంత్ రెడ్డి, టీజేఎస్ అధ్యక్షుడు కోదండ రాం, టీడీపీ తెలంగాణ అధ్యక్షుడు ఎల్.రమణ, సీపీఐ నాయకుడు చాడ వెంకట్ రెడ్డి, బీజేపీ నేత వివేక్, ఎంఆర్పీఎస్ నాయకుడు మంద కృష్ణమాదిగతోపాటు పలు ప్రజా సంఘాలు, రాజకీయ పార్టీల నాయకులు, కళాకారులు, కార్మిక సంఘాల ప్రతినిధులు ఈ సభకు హాజరయ్యారు. సభలో మాట్లాడిన వారంతా ప్రభుత్వ వైఖరిని తప్పు పట్టారు. కార్మికులకు అండగా ఉంటామని భరోసా ఇచ్చారు. ఆర్టీసీని విలీనం చేయడం ఎందుకు సాధ్యం కాదో చెప్పాలని రేవంత్ రెడ్డి ప్రభుత్వాన్ని డిమాండ్ చేశారు. తెలంగాణ సీఎం కేసీఆర్ తీసుకునే నిర్ణయాలు అన్నీ మేనిఫెస్టోలో పెట్టే తీసుకుంటున్నారా అని ప్రశ్నించారు. కార్మికులకు మద్దతుగా ఆందోళనలు చేస్తామని, అవసరమైతే మిలియన్ మార్చ్ నిర్వహిస్తామని కోదండరామ్ హెచ్చరించారు. “కేసీఆర్ ఎన్నో పుస్తకాలు చదివానని చెప్పుకుంటాడు. కానీ, ఆయనకు రాజ్యాంగంపై కూడా అవగాహన లేదు” అని చాడ వెంకటరెడ్డి విమర్శించారు. ఈ సమ్మె విషయంలో కేంద్రం జోక్యం చేసుకోవాలని ఆయన కోరారు. కార్మికుల ఐక్యతను దెబ్బతీయడానికి కేసీఆర్ కుట్రలు పన్నుతున్నారని, కార్మికులు అప్రమత్తంగా ఉండాలని ఎల్.రమణ విజ్ఞప్తి చేశారు. ఆర్టీసీని అన్యాక్రాంతం చేయాలని ప్రభుత్వం ప్రయత్నాలు చేస్తోందని ఆరోపించారు. కేసీఆర్ అవకాశవాది అని, తప్పుడు ప్రచారాలు చేస్తున్నారని బీజేపీ నేత వివేక్ అన్నారు. సకల జన భేరి సభకు హైదరాబాద్‌తో పాటు ఇతర ప్రాంతాలకు చెందిన ఆర్టీసీ సిబ్బంది తరలి వచ్చారు. సభలో కేసీఆర్‌కు వ్యతిరేకంగా నినాదాలు చాలా సార్లు వినిపించాయి. సభా ప్రాంగణం సరిపోక పోవడంతో బయట కూడా పెద్ద సంఖ్యలో కార్మికులు నిలబడిపోయారు. ఆర్టీసీ కార్మికులతో పాటు వామపక్షాల కార్యకర్తలు కూడా సభకు పెద్ద సంఖ్యలో హాజరయ్యారు. ఆర్టీసీ సమ్మె బుధవారానికి 26 రోజులకు చేరుకుంది. ప్రస్తుతానికి సమ్మె ముగిసే సంకేతాలు ఏమీ కనిపించడం లేదు. ప్రభుత్వం, కార్మిక సంఘాలు తమ తమ వాదనలకు కట్టుబడి ఉన్నాయి. ఆర్టీసీపై ముఖ్యమంత్రి కేసీఆర్ బుధవారం సమీక్ష నిర్వహించారు. మరోవైపు, గురువారం అన్ని డిపోల ముందు నిరాహార దీక్షలు చేయాలని ఆర్టీసీ జేఏసీ పిలుపునిచ్చింది. ఇవి కూడా చదవండి: (బీబీసీ తెలుగును ఫేస్‌బుక్, ఇన్‌స్టాగ్రామ్, ట్విటర్‌లో ఫాలో అవ్వండి. యూట్యూబ్‌లో సబ్‌స్క్రైబ్ చేయండి.)

Human: సమ్మె బాట పట్టిన తెలంగాణ ఆర్టీసీ కార్మికులు బుధవారం హైదరాబాద్ లో సకల జనభేరి పేరుతో సభ నిర్వహించారు.

Meta-X_{NLG} : తెలంగాణ ఆర్టీసీ కార్మిక సంఘాల జేఏసీ ఆధ్వర్యంలో జరిగిన సకల జన భేరి సభ హైదరాబాద్ లో జరిగింది.

Bengali-XLSum

Input Document: ভারতের অন্য অঞ্চলেও কোক, পেপসি নিষিদ্ধ করার দাবি জানাচ্ছেন কর্মীরা। স্থানীয় পণ্যের ব্যবহার নিশ্চিত করার জন্যই এই উদ্যোগ গ্রহণ করেছে ব্যবসায়ীরা। রাজ্যের শীর্ষ দুটি ব্যবসায়ী এসোসিয়েশন এই দুটি পানীয় নিষিদ্ধ করার প্রস্তাব করেছিল। তারই প্রেক্ষাপটে আজ বুধবার থেকে তামিলনাড়ু রাজ্যে নিষিদ্ধ হলো কোকা-কোলা ও পেপসি। প্রতিষ্ঠানগুলো বলছে, কোমল পানীয়ের প্রতিষ্ঠানগুলো নদী থেকে প্রচুর পানি ব্যবহার করে, সেকারণে কৃষকদের জমি সেচের সময়ও ব্যাপক ভোগান্তিতে পড়তে হয়। বিশেষ করে খরার সময় সেচে পানি সমস্যা প্রকট হয়ে দাঁড়ায়। রাজ্যের দশ লাখেরও বেশি দোকানদার এ নিষেধাজ্ঞা মেনে চলবে বলে ধারণা করা হচ্ছে। গত মাসে তামিলনাড়ুতে 'জাল্লিকাটু' নামে ঐতিহ্যবাহী ষাঁড়ের লড়াই নিষিদ্ধের বিরুদ্ধে ব্যাপক বিক্ষোভের ঘটনা দেখে রাজ্যে পেপসি, কোকা-কোলা নিষিদ্ধের প্রস্তাব করে শীর্ষ দুটি ব্যবসায়ী সংগঠন ফেডারেশন অব তামিলনাড়ু ট্রেডার্স এসোসিয়েশন (এফটিএনটিএ) এবং তামিলনাড়ু ট্রেডার্স এসোসিয়েশন। বিক্ষোভের সময় অনেকে বলছিলেন 'জাল্লিকাটু' নিষিদ্ধ করা মানে স্থানীয় ঐতিহ্য ও সংস্কৃতিকে অবমাননা করা। \"আমরা কয়েক মাস আগে কোমল পানীয়ের বিরুদ্ধে আমাদের প্রচারণা শুরু করি, কিন্তু যখন আমরা 'জাল্লিকাটু' নিষিদ্ধের প্রতিবাদে বিক্ষোভ শুরু করি, কোমল পানীয়ের বিরুদ্ধে আমাদের প্রচারণাও ভিন্ন রূপ পায়\"- বিবিসি তামিল সার্ভিসকে দেয়া এক সাক্ষাৎকারে বলছিলেন এফটিএনটিএ'র প্রেসিডেন্ট থা ভেলায়ান। \"পেপসি"

Human: ভারতের দক্ষিণাঞ্চলীয় রাজ্য তামিলনাড়ুর ব্যবসায়ীরা সেখানে কোকা-কোলা ও পেপসি বিক্রি নিষিদ্ধ ঘোষণা করেছে।

Meta-X_{NLG} : ভারতের তামিলনাড়ু রাজ্যে কোমল পানীয় নিষিদ্ধ করার দাবি জানিয়েছে ব্যবসায়ীরা।

Hindi-Wikilingua

Input Document: ठंडे पानी से धोते हुए दाग को कुछ हल्का करने की कोशिश करें। ठंडे पानी और एक टॉवल की मदद से धब्बे को गीला कर लें। या फिर, दाग को ठंडे पानी के नीचे भी लगाया जा सकता है। पेस्ट बनाने के लिए एक भाग ठंडा पानी और दो भाग नमक को मिलाएँ। आपको कितने नमक और पानी की जरूरत पड़ने वाली है, ये तो पूरी तरह से उस धब्बे के आकार पर निर्भर करेगा। नमक के साथ में बहुत ज्यादा पानी भी न मिलाएँ, नहीं तो ये लिक्विड बन जाएगा। पेस्ट फैलाने लायक गाढ़ा होना चाहिए। आप चाहें तो पेस्ट को दाग पर लगाने के लिए अपने हाँथ का या एक साफ कपड़े का यूज भी कर सकते हैं। पेस्ट को बहुत आराम से धब्बे के ऊपर रगड़ लें। अब आपको वो दाग हल्का होता हुआ नजर आना चाहिए। जैसे ही, ज़्यादातर या पूरा धब्बा निकल आए, कपड़े को ठंडे पानी के नीचे लगा दें। पेस्ट के पूरे साफ होने तक इसे धोते रहें। अगर दाग अभी तक पूरा नहीं निकल पाया है, तो पेस्ट को फिर से लगा दें। उस कपड़े को धोने के लिए भी उसी साबुन का यूज करें, जिसे आप नॉर्मली यूज किया करते हैं। हालाँकि, कपड़े को धोने के लिए ठंडे पानी के अलावा और किसी चीज़ का यूज बिल्कुल न करें। कपड़े को धो लेने के बाद, इसे हवा में सूखने के लिए लटका दें।

Human: दाग को ठंडे पानी से धो लें: नमक और पानी से एक पेस्ट तैयार करना: पेस्ट को धब्बे पर लगा लें: कपड़े को ठंडे पानी में धो लें: नॉर्मल जैसे ही धो लें:.

Meta-X_{NLG} : धब्बे को ठंडे पानी से धोने के लिए एक टॉवल का यूज कर लें। नमक और पानी का घोल बनाये। धब्बे को घोल से धोये; ठंडे पानी से धोये।

TyDiQA-Tamil

Passage: Coordinates: வால்ட் டிஸ்னி உலகம் (Walt Disney World) அல்லது வோல்ட் டிஸ்னி உலக ஓய்விடம் சுருக்கமாக டிஸ்னி உலகம் என்பது உலகின் மிக அதிகமானோர் செல்லும் சுற்றுலா மற்றும் பொழுதுபோக்கு ஓய்விடமாகும். இது அமெரிக்காவின் புளோரிடாவில் உள்ள பியூனா விஸ்டா என்ற ஏரியில் அமைந்துள்ளது.[1] வால்ட் டிஸ்னி நிறுவனத்தால் பராமரிக்கப்படும் இவ்விடத்தின் பரப்பளவு 30,080 ஏக்கர் (12,173 ஹெக்டயர்; 47 சதுர மைல்) பரப்பளவைக் கொண்டது. வால்ட் டிஸ்னி உலகில் நான்கு கேளிக்கைப் பூங்காக்களும் மற்றும் இரண்டு நீர்ப் பூங்காக்களும், இருப்பத்து நான்கு ஓய்வு விடுதிகளும் மற்றும் இரு ஆரோக்கிய நீரூற்று மற்றம் உடற்பயிற்சி நிலையங்கள், ஐந்து கோல்ப் விளையாட்டிடங்கள் மற்றும் பிற பொழுதுபோக்கு அம்சங்களும் உள்ளன.மேற்கோள்கள் வெளியிணைப்புக்கள்பகுப்பு:சுற்றுலாபகுப்பு:புளோரிடா

Answer: புளோரிடாவில்

Question (Human): டிஸ்னி <u>வேர்ல்ட்</u> எங்கு உள்ளது?

Question (Meta-X_{NLG}): வால்ட் டிஸ்னி <u>உலகம்</u> எங்கே அமைந்துள்ளது?

XQuAD-Hindi

Passage: दक्षिणी कैलिफोर्निया एक संयुक्त सांख्यिकीय क्षेत्र, आठ महानगरीय सांख्यिकीय क्षेत्रों, एक अंतरराष्ट्रीय महानगरीय क्षेत्र और कई महानगरीय डिवीजनों से मिलकर बना हुआ है। इस क्षेत्र में दो विस्तारित महानगरीय क्षेत्र बसे हुए हैं जो जनसंख्या में पांच मिलियन से अधिक हैं। इनके अंतर्गत ग्रेटर लॉस एंजिल्स क्षेत्र में 17,786,419, और सैन डिएगो-तिजुआना में 5,105,768 की आबादी हैं। इन महानगरीय क्षेत्रों में से, लॉस एंजिल्स-लॉन्ग बीच-सांता एना महानगरीय क्षेत्र, नदी के किनारे पर स्थिति-सैन बर्नार्डिनो-ओंटारियो महानगरीय क्षेत्र, और ऑक्सनार्ड-थाउज़ेंड ओक्स-वेंचुरा महानगरीय क्षेत्र मिलकर ग्रेटर लॉस एंजिल्स की रचना करते हैं; जबकि एल सेंट्रो महानगरीय क्षेत्र और सैन डिएगो-कार्ल्सबैड-सैन मार्कोस महानगरीय क्षेत्र दक्षिणी सीमा क्षेत्र बनाते हैं। ग्रेटर लॉस एंजिल्स के उत्तर में सांता बारबारा, सैन लुइस ओबिसपो और बेकर्सफील्ड महानगरीय क्षेत्र आते हैं।

Answer: 17,786,419

Question (Human): ग्रेटर लॉस एंजिल्स क्षेत्र की जनसंख्या कितनी है?

Question (Meta-X_{NLG}): ग्रेटर लॉस एंजिल्स क्षेत्र में कितनी आबादी है?

MLQA-Hindi

Passage: शिकागो विश्वविद्यालय के परिसर की पहली इमारतें, जो अब मुख्य प्रांगण के रूप में जानी जाती हैं, एक \"मास्टर प्लान\" का हिस्सा थीं, जिसकी कल्पना शिकागो विश्वविद्यालय के दो ट्रस्टियों द्वारा की गई थी और जिसे शिकागो के वास्तुकार हेनरी इवेस कॉब द्वारा तैयार किया गया था। मुख्य प्रांगण में छह चौकोर प्रांगण हैं, प्रत्येक प्रांगण एक चौकोर भवन से घिरा होता है, जिसके द्वारा एक बड़े चौकोर प्रांगण की सीमा बनती है। मुख्य प्रांगण की इमारतों को कोब, शेप्ली, रुटान और कूलिज, होलाबर्ड और रोश और अन्य वास्तुकला फर्मों द्वारा डिजाइन किया गया था, जो विक्टोरियन गोथिक और कॉलेजिएट गोथिक शैलियों के मिश्रण के रूप में ऑक्सफोर्ड विश्वविद्यालय के कॉलेजों पर आधारित हैं। (उदाहरण के लिए, मिशेल टॉवर, ऑक्सफोर्ड के मैग्डलेन टॉवर के बाद तैयार की गई है, और यूनिवर्सिटी कॉमन्स, हचिंसन हॉल, क्राइस्ट चर्च हॉल की प्रतिलिपि हैं।

Answer: मुख्य प्रांगण

Question (Human): विश्वविद्यालय द्वारा निर्मित पहली इमारत आज किस नाम से जानी जाती हैं?"

Question (Meta-X_{NLG}): शिकागो विश्वविद्यालय के परिसर की पहली इमारत का क्या नाम है?

Figure 4: Zero-shot samples generated by Meta-X_{NLG} 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 though the reference is in transliterated form. See the underlined token (in red font color) in the TyDiQA-Tamil example.