NIRANTAR: CONTINUAL LEARNING WITH NEW LANGUAGES AND DOMAINS ON REAL-WORLD SPEECH DATA

Anonymous authors
Paper under double-blind review

ABSTRACT

We present Nirantar[1] based on a large-scale effort to collect extempore and conversational speech data from participants spanning 22 languages across diverse locations in India. Given the extensive number of languages and locations involved, data is collected in incremental batches. Each batch introduces new languages, new domains (locations), or both, creating a practical playground for continual learning (CL). Nirantar contains a total of 3250 hours of human-transcribed speech data covering 208 Indian districts across 22 languages, with 1720 hours newly released as a part of this work. The data inflow and resulting multilingual multi-domain episodes are based on real-world data collection rather than simulated episodes commonly found in existing CL datasets. In particular, the amount of data collected and the number of languages and domains involved are not uniform across episodes, reflecting a practical and real-world continual learning scenario. This dataset serves as a playground for training and evaluating CL approaches in three different scenarios: Language-Incremental (LIL), Domain-Incremental (DIL), and the novel Language-Incremental Domain-Incremental Learning (LIDIL), which has not been studied before. To establish the dataset's usefulness, we evaluate several existing CL approaches within these scenarios. Our findings indicate that the behaviour of these algorithms varies across the three scenarios, emphasizing the need for detailed independent studies of each.

1 INTRODUCTION

The availability of ever-expanding datasets (Ardila et al., 2020; Wang et al., 2021b; Chan et al., 2021; Yang et al., 2024b) has facilitated the scaling of speech models (Radford et al., 2023; Zhang et al., 2024), leading to significant advancements in speech technology. Indeed, there is a growing trend towards training massive multilingual speech models on large amounts of data aggregated across multiple languages (Lugosch et al., 2021; Zhang et al., 2023). Given the substantial computational demands of these models, continual training has become crucial as new datasets for additional languages, domains, or demographics are introduced over time (Ardila et al., 2020; Gangwar et al., 2023). To address this, several continual learning techniques have emerged (Wang et al., 2024; Mundt et al., 2023), enabling efficient model updates with new data while preserving performance on previously learned tasks. These methods focus on three broad scenarios, *viz.*, *instance incremental learning*, *task incremental learning* and *domain incremental learning*.

Given the practical importance of Continual Learning (CL), several datasets and benchmarks have been proposed to evaluate the effectiveness of CL methods. However, most of these datasets, such as permuted MNIST (Goodfellow et al., 2014), Split-MNIST (Zenke et al., 2017), and Split-CIFAR (Krizhevsky et al., 2009), are synthetically derived from pre-existing datasets that were not incrementally collected. Since the original datasets were available all at once, there are no natural episodes, and for CL evaluation, episodes are artificially created by arbitrarily dividing the data. This differs significantly from how data arrives episodically in real-world scenarios, rendering these datasets inadequate for evaluating CL methods in such settings. More recently, benchmarks grounded in real-world scenarios, such as CLEAR (Lin et al., 2021), Visual Domain Decathlon

[1] Nirantar in Hindi means continual

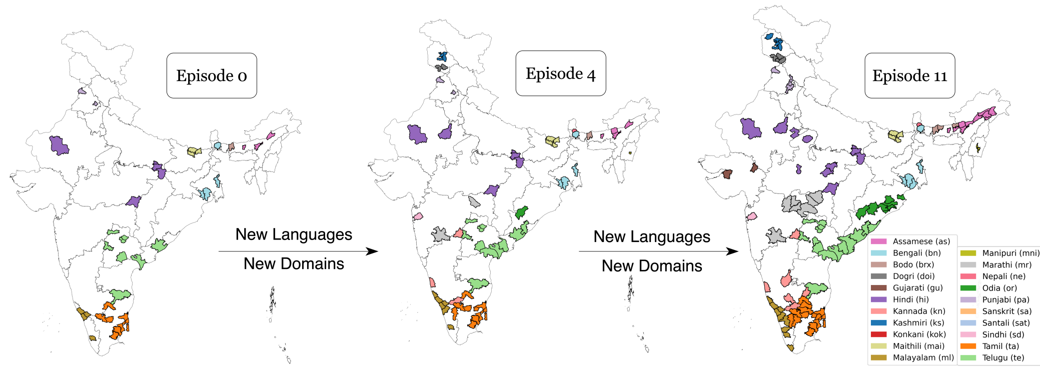


Figure 1: Illustration of Language-Incremental Domain-Incremental Learning: A practical scenario showing the addition of both new languages and domains in each episode of speech data collection. Our proposed episode timeline consists of a sequence of 208 domains across 22 languages.

(Rebuffi et al., 2017), Natural Language Decathlon (McCann et al., 2018), and CLIF (Jin et al., 2021), have been introduced to assess CL techniques. However, these benchmarks typically focus exclusively on either task-incremental learning or domain-incremental learning, and do not simultaneously address both or their combination.

In this work, we consider a practical on-ground speech data collection project for low-resource Indian languages, called IndicVoices (Javed et al., 2024b). This project aims to collect a representative and inclusive multilingual speech dataset covering 22 Indian languages and participants from 400 districts across the country. Data collection happens in batches and is coordinated by a team spread across the country. Specifically, at any given time, one or more districts corresponding to one or more of the 22 languages are identified. Following this, participants from the given district are solicited and asked questions specific to the district, local customs, and their interests. A total of around 20 to 50 hours of data is collected from each district, covering read, extempore, and conversational data on a random subset of topics, domains, and conversational scenarios relevant to that language and district. Each district serves as a domain due to its unique colloquial vocabulary, accents, and interests of local speakers. For example, a participant in Srinagar in northern India may talk about snow-capped mountains, whereas a participant in Assam in northeastern India may talk about tea plantations. Even for a given language, the choice of vocabulary, accents, topics of interest (farming, education, politics, entertainment, travelling, etc.) varies from one district to another.

The episodic nature of the data, with periodic gaps between batches that change language and domain distribution, provides an ideal setting for training and evaluating continual learning methods. Exploiting this natural episodic inflow of data, we create Nirantar, a realistic data framework for training and evaluating CL methods in three different scenarios: Language-Incremental (LIL), Domain-Incremental (DIL), and Language-Incremental Domain-Incremental Learning (LIDIL). The third scenario is novel as shown in Figure 1, and has not been studied in previous works. Nirantar contains a total of 3250 hours of human-transcribed speech data, of which 1530 hours was derived from the training set of the IndicVoices dataset (Javed et al., 2024b) and the remaining 1720 hours were newly collected as a part of this work following the exact same procedure as IndicVoices. The training data is divided into 12 episodes, each containing new languages, new domains, or both. The evaluation data contains 15 minutes of diverse data for each domain and language pair. We intend to maintain this as a live, evolving benchmark by continuously adding 15 minute samples to our test set as more data is collected. Furthermore, given that the test data is sampled at the district level, it naturally allows evaluation in an episodic setting.

We evaluate several existing continual learning (CL) approaches on the Nirantar benchmark, including replay-based methods, such as Experience Replay (Rolnick et al., 2019) and regularization-based methods, such as Elastic Weight Consolidation (Zhou & Cao, 2021) and Memory-aware Synapse (Aljundi et al., 2018). We observe that these approaches demonstrated varying performance across the three continual learning scenarios. This variability suggests that current techniques may not be universally effective, highlighting the need for more robust approaches that can consistently perform well across diverse multilingual and multidomain settings. We also make a key observation regarding architecture-based methods for CL. We found that these methods, which require adding parameters to the backbone, are impractical in real-world scenarios involving multiple languages and domains. Specifically, the addition of each new language (22 in our case) and each new domain (208 in our case) necessitates introducing a new adapter to the model. Over time, this leads to excessive complexity and model bloat, rendering such popular methods infeasible in real-world settings like Nirantar.

To encourage further research, all code, data, and models resulting from this work will be publicly available under the CC-BY-4.0 license. We would like to highlight that the 22 languages covered in Nirantar belong to 4 different language families, with good linguistic diversity. We focus our case study on Indian languages as they provide a good mix of medium-resource (eg, Tamil, Bengali), low-resource (eg. Marathi, Urdu, Konkani) and extremely low-resource (eg. Sindhi, Manipuri) languages. Given this, we believe that the observations made using Nirantar will be relevant for other low-resource language groups, and a broad set of language families as well.

2 RELATED WORK

Prior work in CL is broadly categorized into three types: regularization-based methods, replay-based methods, and architecture-based methods (Wang et al., 2023). Regularization-based methods, such as Elastic Weight Consolidation (EWC) (Zhou & Cao, 2021) and Memory-aware Synapses (MAS) (Aljundi et al., 2018), constrain large updates to model weights. Replay-based methods like Experience Replay (ER) and its variants (Rolnick et al., 2019) store past examples to mitigate forgetting, with enhancements such as Dark Experience Replay (DER) (Buzzega et al., 2020) applying knowledge distillation to stored examples. Averaged Gradient Episodic Memory (A-GEM) (Chaudhry et al., 2019) modifies gradients to minimize interference between new and old tasks. Architecture-based methods like Progressive Neural Networks (PNNs) (Rusu et al., 2016) and PackNet (Mallya & Lazebnik, 2018) allocate parameters for new tasks while preserving old ones.

Continual learning in ASR. In ASR, Continual Learning (CL) has primarily been studied in two settings: Language-Incremental Learning and Domain-Incremental Learning (van de Ven et al., 2022). For instance, Sadhu & Hermansky (2020) propose decomposing a DNN ASR system into sub-models specific to each domain, while Chang et al. (2021) trains a monolingual hybrid CTC-transformer model to adapt to new data distributions. These studies mainly focus on monolingual ASR with a domain incremental setup. In contrast, CL-MASR (Libera et al., 2023) explores various CL strategies in a multilingual setup, examining the potential of large-scale pretrained models in a language (task) incremental setting. Despite these advancements, there has been limited attention to continually updating models in settings that mimic real-world data collection scenarios. Our work offers a more broader playground for assessment of multilingual models by studying all three scenarios of Language-Incremental Learning (LIL), Domain-Incremental Learning (DIL), and Language-Incremental Domain-Incremental Learning (LIDIL).

Continual learning benchmarks. To the best of our knowledge, we are the first to introduce Continual Learning with new languages and new domains for ASR. A similar scenario termed new instances and new classes (NIC) (Lomonaco & Maltoni, 2017; Ceccon et al., 2024) exists but our work adapts it uniquely to the ASR domain by providing a framework that handles continual learning challenges specific to multilingual and multi-domain ASR systems. This benchmark facilitates the comprehensive evaluation of ASR models under more realistic and dynamic conditions, thereby pushing the boundaries of current continual learning research in ASR.

3 NIRANTAR: CONTINUAL LEARNING ON REAL-WORLD SPEECH DATA

In this section, we introduce Nirantar, a playground for continual learning in Automatic Speech Recognition (ASR) with new languages and domains. We also introduce definitions that will be referenced throughout the remainder of this paper.

3.1 Definitions

Data Batch (B): A data batch represents a unit of data collection resulting from a single data gathering activity for a specific domain d of a language l, drawn from a set of domains $\mathcal{D}$ across a collection of languages $\mathcal{L}$. It is represented as an ordered tuple $B = (l, d)$, where $l \in \mathcal{L}$ and $d \in \mathcal{D}$. In ASR, a data batch consists of a set of (x, y) pairs, where x denotes the raw speech signal and y represents the corresponding transcript.

Episode (E): An episode may involve a single data batch (B) or multiple data batches. Typically, the collection of several data batches occurs in parallel. This is represented by a data collection episode E, which is defined as a set of data batches, as follows:

$$E = \{(l, d) \mid l \in \mathcal{L}, d \in \mathcal{D}\} \tag{1}$$

Timeline (T): A timeline T is defined as a sequence of episodes, represented as follows:

$$T = \langle E_0, E_1, \ldots, E_t, \ldots, E_\tau \rangle \tag{2}$$

where t denotes a time step within the timeline and τ represents the total number of episodes.

Model (m): A model m is a learnt mapping $y = m(x)$ by training on a collection of data batches.

Continual Learning Method (c): Given a timeline T, and a base model m_0 obtained by training on E_0, the continual learning method $c(\cdot)$ produces the model m_τ iteratively, as follows -

$$m_t = c(E_t, m_{t-1}), \quad 1 \leq t \leq \tau \tag{3}$$

3.1.1 Continual Learning Scenarios

We now briefly discuss the three continual learning scenarios

Language Incremental Learning (LIL): In the Language-Incremental Learning (LIL) scenario, a new language is added in each episode. Specifically, for a given time step t, an episode E_t consists of all data batches corresponding to a language L_t, as shown below-

$$E_t = \{(L_t, d) \mid d \in \mathcal{D}\}, \quad \forall\, t \in \tau, L_t \in \mathcal{L} \tag{4}$$

Domain Incremental Learning (DIL): In the Domain-Incremental Learning (DIL) scenario, new domains are added in each episode. Specifically, all languages are seen at E_0, as shown below -

$$E_0 = \{(l, d) \mid \cup\, l = \mathcal{L}\} \tag{5}$$

This ensures that no new languages are added in E_t when $1 \leq t \leq \tau$, only new domains are added.

Language-Incremental Domain-Incremental Learning (LIDIL): In the LIDIL scenario, our evaluation framework comprises of a episode that contains both new languages and new districts, as shown in Equation 1. Here, any random collection of data batches forms an episode, and any random sequence of episodes forms a timeline.

3.2 Dataset Description

We build on top of recently released IndicVoices dataset (Javed et al., 2024b), which represents one of the largest efforts to collect speech datasets, covering India's 22 constitutionally recognized languages. It contains read, extempore and conversational data from a diverse set of speakers with fair representation across age groups, genders, educational backgrounds, locations and occupations. We further improve on IndicVoices to build Nirantar, to enable training and evaluation of ASR systems in a continual learning scenario. Specifically, apart from the initial 1530 hours released as part of IndicVoices, we collect an additional 1720 hours as a part of this work, using the exact same procedure as the original work. We collected the data in phases with each phase involving collection of data batches in parallel from one or more districts for one or more languages. Our team of coordinators visited each district, and mobilised around 100-150 participants with the help of local partners. After taking consent from the participants and appropriately compensating them for

Table 1: Number of hours (#H), speakers (#Sp), and domains (#D) in Nirantar, along with the ISO codes for the languages.

	iso	#H	#Sp	#D		iso	#H	#Sp	#D
Assamese	as	241	985	14	**Manipuri**	mni	42	166	3
Bengali	bn	209	733	11	**Marathi**	mr	118	447	10
Bodo	brx	291	1061	4	**Nepali**	ne	252	780	4
Dogri	doi	116	495	5	**Odia**	or	124	473	9
Gujarati	gu	20	72	4	**Punjabi**	pa	124	344	6
Hindi	hi	138	490	12	**Sanskrit**	sa	70	222	17
Kannada	kn	96	530	13	**Santali**	sat	164	433	8
Konkani	kok	103	245	4	**Sindhi**	sd	27	240	4
Kashmiri	ks	106	515	10	**Tamil**	ta	238	1242	19
Maithili	mai	248	726	9	**Telugu**	te	221	767	28
Malayalam	ml	170	504	10	**Urdu**	ur	124	564	10

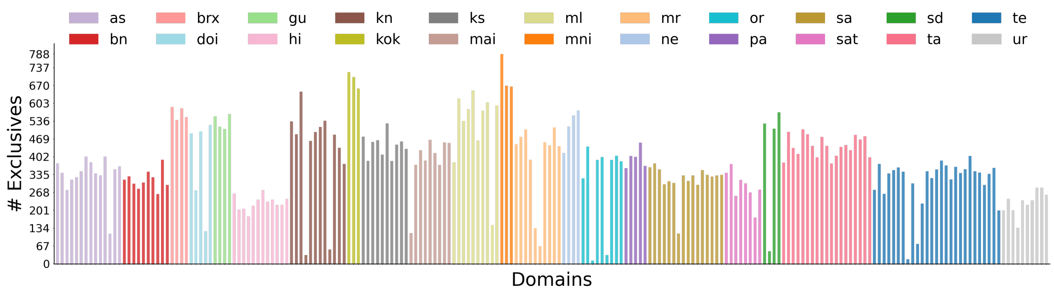


Figure 2: Number of unique words across each of the domains (districts) for all 22 Indian languages

their time, the coordinators recorded their (i) responses to tailored questions based on their topics of interest (ii) simulated interactions with voice assistants for everyday tasks like hailing a cab, making online payments, ordering food, etc. and (iii) two-party telephony interactions with other paid participants. The data was then transcribed with the help of an in-house team of transcribers comprising of makers, checkers and super-checkers to ensure quality.

Data collected from each district is treated as a batch and several data batches are aggregated to form a data episode. Each episode thus contains data from one or more languages consisting of one or more districts. Here, we consider each district as a new domain as the data characteristics vary from one district to another due to variation in accents, colloquial vocabulary, topics on interest and responses to questions which are specific to the given district. For example, as shown in Figure 2, the vocabulary usage changes across districts as indicated by the number of unique words added in each new district (each color corresponds to a different language). Nirantar thus leverages the natural influx of audio data in batches and splices the audio speech data across multiple timelines, one each for LIL, DIL, LIDIL. The creation of the timelines is highlighted in Section 3.3. Nirantar contains 3250 hours of data covering 208 districts across 22 Indian languages. Table 1 presents the statistics of data across languages. For creating the test data, we sample a maximum of 15 minutes from each of the domains resulting in a total of 50 hours across languages. Since the test data contains samples from every district, we can evaluate the forward and backward transfer of CL approaches.

3.3 Continual Learning Playground

The Nirantar playground comprises three distinct timelines corresponding to LIL, DIL and LIDIL scenarios respectively. Table 2 outlines the distribution of data batches. Next, we present the process of creation of the timelines.

Base episode (E_0): In a practical scenario, the base model (m_0) will be trained after a seed amount of data is collected. We consider a good starting point for the base episode (E_0) when data batches are collected for half of the languages and half of the domains in each language. With this in mind, for LIDIL, we select the 11 languages having the largest number of hours in Table 1, and randomly

Table 2: Statistics showing the number of districts per language and the corresponding total number of hours (# H) of data for each episode (Ep) across LIL, DIL, and LIDIL settings. Each row represents an episode.

Ep	Languages																						#H
	as	bn	brx	doi	gu	hi	kn	kok	ks	mai	ml	mni	mr	ne	or	pa	sa	sat	sd	ta	te	ur	
LIL																							
0	14	11	4	-	-	12	-	-	-	9	10	-	-	4	-	6	-	8	-	19	28	-	2248
1	-	-	-	5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	113
2	-	-	-	-	-	-	-	-	10	-	-	-	-	-	-	-	-	-	-	-	-	-	121
3	-	-	-	-	4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	100
4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	10	121
5	-	-	-	-	-	-	-	4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	115
6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	9	-	-	-	-	-	-	-	94
7	-	-	-	-	-	-	-	-	-	-	-	-	10	-	-	-	-	-	-	-	-	-	40
8	-	-	-	-	-	-	13	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	68
9	-	-	-	-	-	-	-	-	-	-	-	3	-	-	-	-	-	-	-	-	-	-	26
10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	17	-	-	-	-	-	103
11	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	4	-	-	-	19
DIL																							
0	7	5	2	2	2	6	6	2	5	4	5	1	5	2	4	3	8	4	2	9	14	5	1610
1	-	-	-	1	-	-	3	-	1	-	1	-	1	1	-	-	-	-	-	1	1	-	244
2	1	-	-	-	-	-	-	-	1	1	1	-	2	1	1	-	-	-	2	-	1	-	153
3	1	-	-	1	-	1	-	-	-	-	1	-	-	-	1	-	-	-	-	1	3	-	104
4	1	-	-	-	1	1	-	-	-	1	-	1	-	-	-	-	-	-	-	1	3	-	36
5	-	-	1	-	1	-	1	-	-	-	-	-	-	-	-	-	-	-	-	1	-	1	125
6	1	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	-	1	1	120
7	-	1	-	1	-	-	-	1	1	-	-	-	-	-	-	2	-	-	-	-	-	-	114
8	1	-	-	-	-	2	1	-	-	-	-	-	-	-	-	1	-	-	-	1	1	1	51
9	-	1	1	-	-	-	-	-	1	-	1	-	-	-	-	-	1	-	-	-	1	-	436
10	-	-	-	-	-	-	1	1	-	-	1	-	1	-	-	-	1	-	-	2	-	-	135
11	2	4	-	-	-	2	1	-	-	3	-	1	1	-	3	-	7	4	-	3	3	2	42
LIDIL																							
0	7	5	2	-	-	6	-	-	-	4	5	-	-	2	-	3	-	4	-	9	14	-	1041
1	-	-	-	-	-	1	-	-	3	-	1	-	1	-	2	-	2	1	1	-	-	-	120
2	-	-	-	2	-	-	2	-	1	1	-	-	-	-	-	-	2	-	-	1	-	-	149
3	1	-	-	-	-	-	1	-	-	-	-	-	1	1	-	-	3	-	1	-	2	1	89
4	-	1	-	-	-	-	2	-	1	2	-	1	1	-	-	-	1	-	-	1	3	1	210
5	-	1	-	-	-	1	1	-	-	1	-	-	1	-	-	-	3	-	1	-	2	-	177
6	2	1	1	-	1	1	1	-	-	-	2	-	-	-	-	1	1	1	-	2	1	1	117
7	-	2	-	2	1	1	-	-	1	-	-	1	-	-	-	-	-	1	1	1	2	2	348
8	-	-	-	-	-	-	2	-	-	1	-	-	-	-	3	-	1	-	-	1	1	1	245
9	1	-	-	-	1	-	1	1	-	-	-	-	4	1	2	1	2	-	-	-	1	-	339
10	3	-	-	-	-	1	2	2	1	-	2	1	1	-	1	-	1	1	-	-	2	3	140
11	-	1	1	1	1	1	1	1	3	-	-	-	1	-	1	1	1	-	-	4	-	1	194

sample half the number of domains in each of these languages to create E_0. For LIL, we start with the same set of 11 languages, having all domains of the respective languages. For DIL, we start with all 22 languages, and randomly sample half the number of domains in each language.

Incremental episodes ($E_{\tau \geq 1}$): We create timelines of length $\tau = 11$. For LIL, all data batches corresponding to one language are added in each episode. The order of the languages is chosen randomly. For DIL and LIDIL, each data batch is randomly assigned to an episode. This ensures uniform distribution of data batches across episodes, while still ensuring non-uniformity in number of training hours across episodes, as shown in Table 2.

The purpose of this playground is to find an optimal continual learning approach c^* given a timeline T and a model m_0. Specifically, $c^* = \min_{c \in \mathcal{C}} V(c \mid T, m)$, where V is a verifier or a metric that evalutes the continual learning approach, and $\mathcal{C}$ is a family of continual learning approaches. We explore a set of continual learning approaches and a set of metrics in Section 4 of the paper.

4 Experimental setup

We now describe the experimental setup used for training various models and evaluating their performance on Nirantar.

4.1 Continual Learning Methods

Referring to the recently released survey paper (Mundt et al., 2023), we note that there are three main categories of popular continual learning (CL) methods, *viz.*, replay based methods, regularisation based methods and architecture-based methods. After careful consideration, we find that, architecture-based methods are not suited for real-world scenarios like Nirantar. This is because they require adding parameters for each new language (22, in our case) and each new domain (208, in our case) leading to excessive complexity and significant model expansion as the number of episodes grows. Given these limitations of architecture-based approaches, in this work, we focus on widely adopted and scalable CL techniques involving replay-based and regularization-based strategies. Below, we list down all the approaches considered in this work.

Incremental Finetuning (Inc. FT): Given a base model m_0, we sequentially finetune models $m_{1 \leq t \leq \tau}$ using the data batches in E_t, and initializing the weights of m_t using the trained model m_{t-1}.

Joint Finetuning (Joint FT): Similar to Incremental Finetuning, we sequentially finetune $m_{1 \leq t \leq \tau}$ by initializing the weights of m_t using the trained model m_{t-1}, but by taking all data batches from $\bigcup_{i=0}^{t} \{E_i\}$.

Elastic Weight Consolidation (EWC) (Zhou & Cao, 2021): EWC performs regularization by preserving important parameters from previous episodes while adapting to new ones. It estimates parameter importance using the Fisher information matrix (F) and adds a penalty term to the loss function during training on the current task. This penalty term, controlled by hyperparameters λ and α, balances between adapting to new tasks and retaining old knowledge. Following Libera et al. (2023) we set λ to 5 and α to 0.5.

Experience Replay (ER) (Rolnick et al., 2019): Experience replay is a replay-based approach that stores data from previous episodes in a memory buffer and replays them during the training of models on current episodes. Following Libera et al. (2023), we sample 3% of data across each episode.

Memory-aware Synapse (MAS) (Aljundi et al., 2018): Like EWC, this method confines large model updates to weights. However, unlike the Fisher information matrix, it assesses parameter importance using the average magnitude of gradients of the squared L2 norm of the learned function. Following Libera et al. (2023), we set α and λ to 1 and 0.5, respectively. These values determine the relative strength of the regularization term and the influence of previous tasks on updating parameter importance.

4.2 Training

We train Conformer-L (Gulati et al., 2020) models, consisting of 120M parameters, as the encoder, with a hybrid CTC-RNNT (Noroozi et al., 2023) decoder. The model has 17 conformer blocks with 512 as the model dimension. The output vocabulary is of size 256 per language, and is created by a Byte-Pair-Encoding (BPE) tokenizer. Each language consists of a separate decoder head. All our models are trained using the NeMo (Kuchaiev et al., 2019) library. The base models m_0 and the Joint FT models were trained for 150,000 steps with a constant learning rate of 0.0001. Due to the skew in data distribution across languages in our joint multilingual setup, we found temperature sampling to be crucial for model convergence. We trained the incremental models for 30,000 steps with half the learning rate. We trained the models using the Adam optimizer with an effective batch size of 8 audios per GPU. All experiments utilized a total compute of 240 GPU-hours on 8 40GB-A100 GPUs.

4.3 Metrics

To study and compare performance across different continual strategies, we follow Libera et al. (2023) and use the following metrics:

Average MER: Match Error Rate (MER) (Morris et al., 2004) measures the probability of match being incorrect between the predicted transcript and the ground truth transcript. The overall perfor-

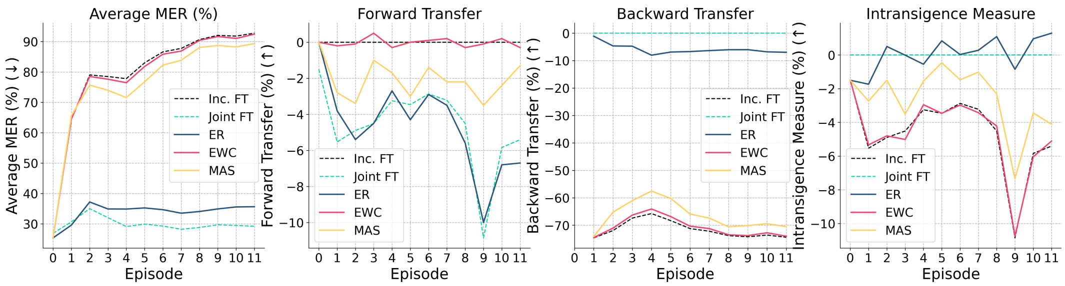


Figure 3: **Language-Incremental Learning (LIL)**: Comparison of various CL methods

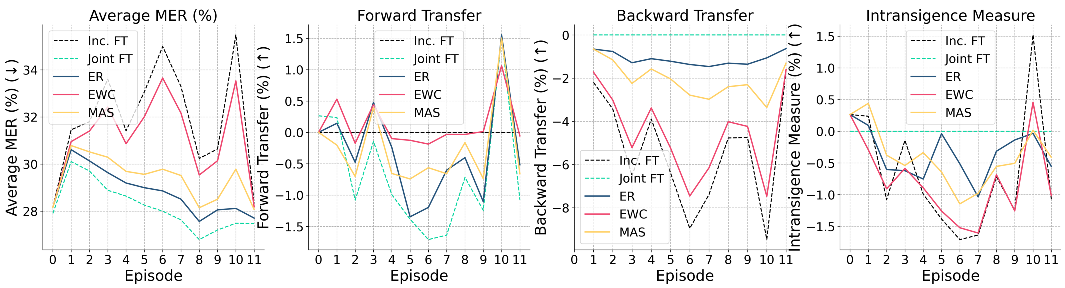


Figure 4: **Domain-Incremental Learning (DIL)**: Comparison of various CL methods

mance across all the seen episodes is calculated by

$$AMER_t = \frac{1}{t}\sum_{i=1}^{t} MER_{t,i}, \quad t \in [0, \tau]$$

Forward Transfer: This metric aims to capture the influence of previous episodes on the model's performance on the current episode. Specifically, it aims to quantify if the model is able to use the knowledge from the previous episode to help in improving the performance on the test set corresponding to the current episode. This metric is denoted by FWT and given by the following equation:

$$FWT_t = MER_t^{inc.ft} - MER_{t,t}$$

Backward Transfer: This quantifies the detriment in the model's performance on the knowledge learned from the previous episodes while learning new tasks and is given by the following equation:

$$BWT_t = \frac{1}{t-1}\sum_{i=1}^{t-1} MER_{i,i} - MER_{t,i}, \quad t \in [1, \tau]$$

Intransigence Measure: It quantifies the plasticity of the models, which refers to the model's capacity to acquire new knowledge effectively, as given by the following equation:

$$IM_t = MER_{t,t} - MER_t^{jointft}$$

5 Results and Discussions

5.1 Comparison of Continual Learning Methods across the 3 scenarios

Figures 3, 4 and 5 present the main results of our study, comparing three continual learning (CL) approaches — ER, EWC, and MAS — across three scenarios: LIL, DIL, and LIDIL.

LIL: Referring to Figure 3, we observe a steady increase in AMER as new languages are introduced for Incremental FT. This is undesirable and highlights the need for effective continual learning (CL) methods. Both regularization-based approaches, EWC and MAS, struggle to retain knowledge of

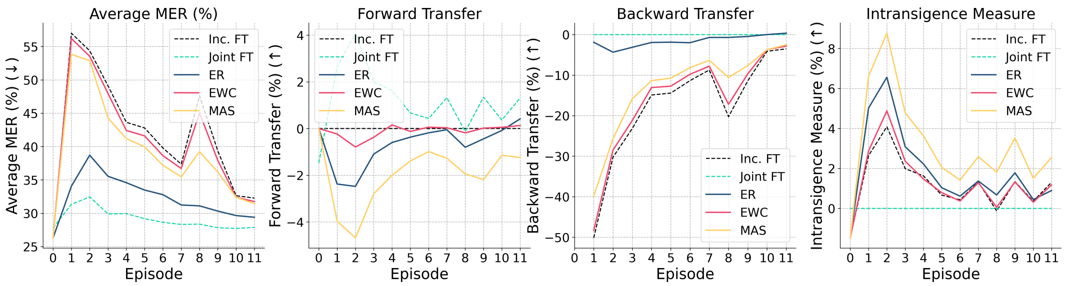


Figure 5: **Language-Incremental Domain-Incremental Learning (LIDIL)**: Comparison of various CL methods

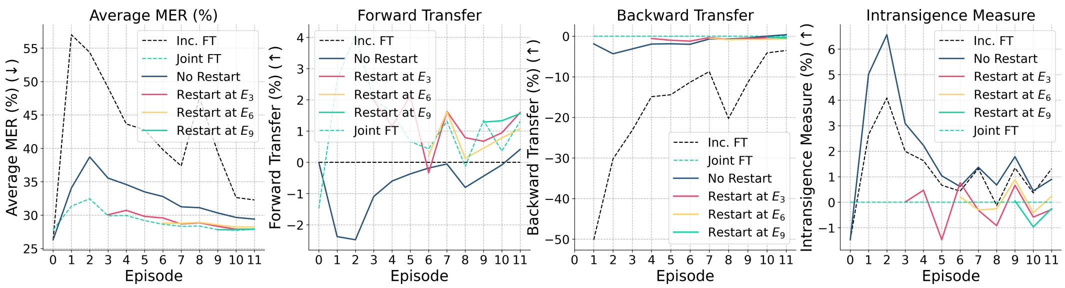


Figure 6: **ER with restarts for LIDIL**: Comparison across restarts from episodes 3, 6 and 9.

previously learned languages, as shown by the trends in the Forward Transfer across episodes. In contrast, ER significantly outperforms them, even with a buffer size of just 3%, demonstrating the importance of replay in LIL. While ER demonstrates strong backward transfer and positive intransigence, its poor forward transfer further emphasizes the need for CL approaches that better leverage knowledge from previous episodes. We also observe a sharp drop in the forward transfer and intransigence measures at episode 9. We hypothesize that this decline is due to the introduction of Manipuri, a Tibeto-Burman language with only 26 hours of data. The limited data and its notable differences from the Indo-Aryan and Dravidian language families observed in earlier episodes are likely factors contributing to this decline.

DIL: Referring to Figure 4, unlike LIL, we observe that AMER reduces over episodes for two methods, MAS and ER. The reduction of AMER over episodes could be attributed to (i) current CL methods being able to adapt better to new domains than to new languages, and (ii) the slightly favorable scenario in DIL, where the base model has already seen all the languages. This indicates the need of better base models to be used for CL. All CL approaches demonstrate good forward transfer and intransigence measure in DIL. The observed performance change of only 1.5% is due to the randomness in the order of incoming data batches. This indicates that knowledge from previous domains is indeed helpful for new domains. Although MAS performs significantly poor in LIL, we observe that it shows good Forward Transfer and Backward Transfer in DIL, showing that regularization-based methods are well suited for domain-incremental learning.

LIDIL: In Figure 5, we observe across all methods that the AMER first increases in the first 2 episodes similar to LIL, and then steadily decreases from episode 3 onwards, similar to DIL. This is due to the fact that many new languages are seen in the first 2 episodes, and the number of new languages gradually reduces after that. This demonstrates the unique hybrid nature of this newly introduced continual learning scenario that encompasses characteristics from both the aforementioned scenarios, *viz.*, LIL and DIL. We also observe that the backward transfer for EWC and MAS improves over time, unlike the other two paradigms, showing that the methods gradually adapt to previous tasks after addition of new languages and domains. All methods show a positive Intransigence Measure in LIDIL.

5.2 Effect of Restarting

As observed in values of average MER in LIDIL for various CL methods, once the model training diverges in a certain episode, it is difficult for the model to catch up. In such cases, it is better to perform a Joint FT. To study this, we allow the CL methods to perform a 'restart' at episodes 3, 6 and 9. Specifically, at these episodes, we start with a base model which has been jointly trained on all data up to this point followed by continual training with ER for the remaining episodes. Figure 6 highlights the results for different restart points for the LIDIL scenario. As seen in Figure 6, restarting leads to more stable training across episodes, allowing the model to recover from earlier divergence. This shows that using a simple and practical technique of restarting, we get a performance which is as good as Joint FT. Specifically, ER restarted at any of these three episodes yielded results that match with the performance of Joint FT.

Performance and Efficiency While the AMER for the Jointly Fine-Tuned models is the lowest, these models are the least efficient in terms of computational resources, as they require retraining on each episode. Conversely, the AMER of Incremental models is the highest in each episode due to catastrophic forgetting. Models with restarts fall in between, and offer a tradeoff between performance and efficiency. For example, models restarted at episode 3 are more performant but less efficient than those restarted at episode 6.

While we understand that restarting essentially undermines the core principle of continual learning, we intentionally include this in our work to show that continual learning methods are still not competitive to restarting (Joint FT) in the LIDIL setting. We conduct this experiment to address a practical situation where training from scratch for each episode is infeasible; however, there is some additional computational budget available for a single restart.

6 Conclusion

We presented Nirantar, a novel data framework designed to facilitate training and evaluation of continual learning (CL) methods in multilingual and multidomain settings. This dataset contains 3250 hours of human-transcribed speech data, including 1720 hours released for this study, organized into 12 episodes featuring diverse language and domain combinations. Evaluations using established CL methods such as Elastic Weight Consolidation, Memory-aware Synapse, and Experience Replay highlight the utility of the dataset across Language-Incremental (LIL), Domain-Incremental (DIL), and Language-Incremental Domain-Incremental Learning (LIDIL) scenarios. All associated resources are available under a CC-BY-4 license to support further research in this area.

7 Ethics

The data collection process follows the same guidelines as IndicVoices (Javed et al., 2024b) and was thoroughly reviewed and approved by the Institute Ethics Committee. Participants were fully informed about the collection, their involvement, and the use of their data, and their consent was obtained beforehand. They received compensation aligned with local daily wages for their time and effort. No PII data will be shared externally, and measures were implemented to anonymize and protect sensitive information. Project staff were also compensated appropriately. Nirantar will be released under the CC-BY-4.0 license, permitting commercial use.

References

2015 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2015, South Brisbane, Queensland, Australia, April 19-24, 2015, 2015. IEEE. ISBN 978-1-4673-6997-8. URL `https://ieeexplore.ieee.org/xpl/conhome/7158221/proceeding`.

Resources for indian languages. 2016. URL `https://api.semanticscholar.org/CorpusID:198919737`.

Madhavaraj A, Bharathi Pilar, and Ramakrishnan A G. Subword dictionary learning and segmentation techniques for automatic speech recognition in tamil and kannada, 2022a. URL `https://arxiv.org/abs/2207.13331`.

Madhavaraj A, Bharathi Pilar, and Ramakrishnan A G. Knowledge-driven subword grammar modeling for automatic speech recognition in tamil and kannada, 2022b. URL https://arxiv.org/abs/2207.13333.

Basil Abraham, Danish Goel, Divya Siddarth, Kalika Bali, Manu Chopra, Monojit Choudhury, Pratik Joshi, Preethi Jyothi, Sunayana Sitaram, and Vivek Seshadri. Crowdsourcing speech data for low-resource languages from low-income workers. In *Proceedings of the 12th Conference on Language Resources and Evaluation (LREC)*, pp. 2819–2826, 2020.

Devaraja Adiga, Rishabh Kumar, Amrith Krishna, Preethi Jyothi, Ganesh Ramakrishnan, and Pawan Goyal. Automatic speech recognition in Sanskrit: A new speech corpus and modelling insights. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli (eds.), *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pp. 5039–5050, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-acl.447. URL https://aclanthology.org/2021.findings-acl.447.

Rahaf Aljundi, Francesca Babiloni, Mohamed Elhoseiny, Marcus Rohrbach, and Tinne Tuytelaars. Memory aware synapses: Learning what (not) to forget. In Vittorio Ferrari, Martial Hebert, Cristian Sminchisescu, and Yair Weiss (eds.), *Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part III*, volume 11207 of *Lecture Notes in Computer Science*, pp. 144–161. Springer, 2018. doi: 10.1007/978-3-030-01219-9_9. URL https://doi.org/10.1007/978-3-030-01219-9_9.

Rosana Ardila, Megan Branson, Kelly Davis, Michael Kohler, Josh Meyer, Michael Henretty, Reuben Morais, Lindsay Saunders, Francis Tyers, and Gregor Weber. Common voice: A massively-multilingual speech corpus. In Nicoletta Calzolari, Frédéric Béchet, Philippe Blache, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, Hitoshi Isahara, Bente Maegaard, Joseph Mariani, Hélène Mazo, Asuncion Moreno, Jan Odijk, and Stelios Piperidis (eds.), *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pp. 4218–4222, Marseille, France, May 2020. European Language Resources Association. ISBN 979-10-95546-34-4. URL https://aclanthology.org/2020.lrec-1.520.

Timo Baumann, Arne Köhn, and Felix Hennig. The spoken wikipedia corpus collection: Harvesting, alignment and an application to hyperlistening. *Lang. Resour. Evaluation*, 53(2): 303–329, 2019. doi: 10.1007/S10579-017-9410-Y. URL https://doi.org/10.1007/s10579-017-9410-y.

Anish Bhanushali, Grant Bridgman, Deekshitha G, Prasanta Kumar Ghosh, Pratik Kumar, Saurabh Kumar, Adithya Raj Kolladath, Nithya Ravi, Aaditeshwar Seth, Ashish Seth, Abhayjeet Singh, Vrunda N. Sukhadia, Srinivasan Umesh, Sathvik Udupa, and Lodagala V. S. V. Durga Prasad. Gram vaani ASR challenge on spontaneous telephone speech recordings in regional variations of hindi. In Hanseok Ko and John H. L. Hansen (eds.), *23rd Annual Conference of the International Speech Communication Association, Interspeech 2022, Incheon, Korea, September 18-22, 2022*, pp. 3548–3552. ISCA, 2022. doi: 10.21437/INTERSPEECH.2022-11371. URL https://doi.org/10.21437/Interspeech.2022-11371.

Kaushal Bhogale, Abhigyan Raman, Tahir Javed, Sumanth Doddapaneni, Anoop Kunchukuttan, Pratyush Kumar, and Mitesh M. Khapra. Effectiveness of mining audio and text pairs from public data for improving asr systems for low-resource languages. In *ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1–5, 2023a. doi: 10.1109/ICASSP49357.2023.10096933.

Kaushal Santosh Bhogale, Sairam Sundaresan, Abhigyan Raman, Tahir Javed, Mitesh M. Khapra, and Pratyush Kumar. Vistaar: Diverse benchmarks and training sets for indian language asr. *ArXiv*, abs/2305.15386, 2023b. URL https://api.semanticscholar.org/CorpusID:258866210.

Pietro Buzzega, Matteo Boschini, Angelo Porrello, Davide Abati, and Simone Calderara. Dark experience for general continual learning: a strong, simple baseline. In Hugo Larochelle, Marc'Aurelio Ranzato, Raia Hadsell, Maria-Florina Balcan, and Hsuan-Tien Lin (eds.), *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12,* *2020, virtual*, 2020. URL https://proceedings.neurips.cc/paper/2020/hash/b704ea2c39778f07c617f6b7ce480e9e-Abstract.html.

Marina Ceccon, Davide Dalle Pezze, Alessandro Fabris, and Gian Antonio Susto. Multi-label continual learning for the medical domain: A novel benchmark. *CoRR*, abs/2404.06859, 2024. doi: 10.48550/ARXIV.2404.06859. URL https://doi.org/10.48550/arXiv.2404.06859.

William Chan, Daniel Park, Chris Lee, Yu Zhang, Quoc Le, and Mohammad Norouzi. Speechstew: Simply mix all available speech recognition data to train one large neural network. *arXiv preprint arXiv:2104.02133*, 2021.

Heng-Jui Chang, Hung-yi Lee, and Lin-Shan Lee. Towards lifelong learning of end-to-end ASR. In Hynek Hermansky, Honza Cernocký, Lukás Burget, Lori Lamel, Odette Scharenborg, and Petr Motlícek (eds.), *Interspeech 2021, 22nd Annual Conference of the International Speech Communication Association, Brno, Czechia, 30 August - 3 September 2021*, pp. 2551–2555. ISCA, 2021. doi: 10.21437/INTERSPEECH.2021-563. URL https://doi.org/10.21437/Interspeech.2021-563.

Arslan Chaudhry, Marc'Aurelio Ranzato, Marcus Rohrbach, and Mohamed Elhoseiny. Efficient lifelong learning with A-GEM. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*. OpenReview.net, 2019. URL https://openreview.net/forum?id=Hkf2_sC5FX.

Alexis Conneau, Min Ma, Simran Khanuja, Yu Zhang, Vera Axelrod, Siddharth Dalmia, Jason Riesa, Clara Rivera, and Ankur Bapna. Fleurs: Few-shot learning evaluation of universal representations of speech, 2022.

Anuj Diwan, Rakesh Vaideeswaran, Sanket Shah, Ankita Singh, Srinivasa Raghavan, Shreya Khare, Vinit Unni, Saurabh Vyas, Akash Rajpuria, Chiranjeevi Yarra, Ashish Mittal, Prasanta Kumar Ghosh, Preethi Jyothi, Kalika Bali, Vivek Seshadri, Sunayana Sitaram, Samarth Bharadwaj, Jai Nanavati, Raoul Nanavati, Karthik Sankaranarayanan, Tejaswi Seeram, and Basil Abraham. Multilingual and code-switching asr challenges for low resource indian languages. *Proceedings of Interspeech*, 2021.

Arjun Gangwar, S Umesh, Rithik Sarab, Akhilesh Kumar Dubey, Govind Divakaran, Suryakanth V Gangashetty, et al. Spring-inx: A multilingual indian language speech corpus by spring lab, iit madras. *arXiv preprint arXiv:2310.14654*, 2023.

Ian J. Goodfellow, Mehdi Mirza, Xia Da, Aaron C. Courville, and Yoshua Bengio. An empirical investigation of catastrophic forgeting in gradient-based neural networks. In Yoshua Bengio and Yann LeCun (eds.), *2nd International Conference on Learning Representations, ICLR 2014, Banff, AB, Canada, April 14-16, 2014, Conference Track Proceedings*, 2014. URL http://arxiv.org/abs/1312.6211.

Anmol Gulati, James Qin, Chung-Cheng Chiu, Niki Parmar, Yu Zhang, Jiahui Yu, Wei Han, Shibo Wang, Zhengdong Zhang, Yonghui Wu, and Ruoming Pang. Conformer: Convolution-augmented transformer for speech recognition. In Helen Meng, Bo Xu, and Thomas Fang Zheng (eds.), *Interspeech 2020, 21st Annual Conference of the International Speech Communication Association, Virtual Event, Shanghai, China, 25-29 October 2020*, pp. 5036–5040. ISCA, 2020. doi: 10.21437/INTERSPEECH.2020-3015. URL https://doi.org/10.21437/Interspeech.2020-3015.

Naomi Harte, Julie Carson-Berndsen, and Gareth Jones (eds.). *24th Annual Conference of the International Speech Communication Association, Interspeech 2023, Dublin, Ireland, August 20-24, 2023*, 2023. ISCA. doi: 10.21437/INTERSPEECH.2023. URL https://doi.org/10.21437/Interspeech.2023.

Fei He, Shan-Hui Cathy Chu, Oddur Kjartansson, Clara Rivera, Anna Katanova, Alexander Gutkin, Isin Demirsahin, Cibu Johny, Martin Jansche, Supheakmungkol Sarin, and Knot Pipatsrisawat. Open-source multi-speaker speech corpora for building Gujarati, Kannada, Malayalam, Marathi, Tamil and Telugu speech synthesis systems. In Nicoletta Calzolari, Frédéric Béchet, Philippe

Blache, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, Hitoshi Isahara, Bente Maegaard, Joseph Mariani, Hélène Mazo, Asuncion Moreno, Jan Odijk, and Stelios Piperidis (eds.), *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pp. 6494–6503, Marseille, France, May 2020. European Language Resources Association. ISBN 979-10-95546-34-4. URL https://aclanthology.org/2020.lrec-1.800.

François Hernandez, Vincent Nguyen, Sahar Ghannay, Natalia A. Tomashenko, and Yannick Estève. TED-LIUM 3: Twice as much data and corpus repartition for experiments on speaker adaptation. In Alexey Karpov, Oliver Jokisch, and Rodmonga Potapova (eds.), *Speech and Computer - 20th International Conference, SPECOM 2018, Leipzig, Germany, September 18-22, 2018, Proceedings*, volume 11096 of *Lecture Notes in Computer Science*, pp. 198–208. Springer, 2018. doi: 10.1007/978-3-319-99579-3_21. URL https://doi.org/10.1007/978-3-319-99579-3_21.

Tahir Javed, Kaushal Bhogale, Abhigyan Raman, Pratyush Kumar, Anoop Kunchukuttan, and Mitesh M. Khapra. Indicsuperb: a speech processing universal performance benchmark for indian languages. In *Proceedings of the Thirty-Seventh AAAI Conference on Artificial Intelligence and Thirty-Fifth Conference on Innovative Applications of Artificial Intelligence and Thirteenth Symposium on Educational Advances in Artificial Intelligence*, AAAI'23/IAAI'23/EAAI'23. AAAI Press, 2023a. ISBN 978-1-57735-880-0. doi: 10.1609/aaai.v37i11.26521. URL https://doi.org/10.1609/aaai.v37i11.26521.

Tahir Javed, Sakshi Joshi, Vignesh Nagarajan, Sai Sundaresan, Janki Nawale, Abhigyan Raman, Kaushal Bhogale, Pratyush Kumar, and Mitesh M. Khapra. Svarah: Evaluating English ASR Systems on Indian Accents. In *Proc. INTERSPEECH 2023*, pp. 5087–5091, 2023b. doi: 10.21437/Interspeech.2023-2588.

Tahir Javed, Janki Nawale, Sakshi Joshi, Eldho Ittan George, Kaushal Santosh Bhogale, Deovrat Mehendale, and Mitesh M. Khapra. LAHAJA: A robust multi-accent benchmark for evaluating hindi ASR systems. *CoRR*, abs/2408.11440, 2024a. doi: 10.48550/ARXIV.2408.11440. URL https://doi.org/10.48550/arXiv.2408.11440.

Tahir Javed, Janki Atul Nawale, Eldho Ittan George, Sakshi Joshi, Kaushal Santosh Bhogale, Deovrat Mehendale, Ishvinder Virender Sethi, Aparna Ananthanarayanan, Hafsah Faquih, Pratiti Palit, Sneha Ravishankar, Saranya Sukumaran, Tripura Panchagnula, Sunjay Murali, Kunal Sharad Gandhi, Ambujavalli R, Manickam K. M, C. Venkata Vaijayanthi, Krishnan Srinivasa Raghavan Karunganni, Pratyush Kumar, and Mitesh M. Khapra. Indicvoices: Towards building an inclusive multilingual speech dataset for indian languages. *CoRR*, abs/2403.01926, 2024b. doi: 10.48550/ARXIV.2403.01926. URL https://doi.org/10.48550/arXiv.2403.01926.

Xisen Jin, Bill Yuchen Lin, Mohammad Rostami, and Xiang Ren. Learn continually, generalize rapidly: Lifelong knowledge accumulation for few-shot learning. In Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2021*, pp. 714–729, Punta Cana, Dominican Republic, November 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.findings-emnlp.62. URL https://aclanthology.org/2021.findings-emnlp.62.

Oddur Kjartansson, Supheakmungkol Sarin, Knot Pipatsrisawat, Martin Jansche, and Linne Ha. Crowd-Sourced Speech Corpora for Javanese, Sundanese, Sinhala, Nepali, and Bangladeshi Bengali. In *Proc. The 6th Intl. Workshop on Spoken Language Technologies for Under-Resourced Languages (SLTU)*, pp. 52–55, Gurugram, India, August 2018. URL http://dx.doi.org/10.21437/SLTU.2018-11.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

Oleksii Kuchaiev, Jason Li, Huyen Nguyen, Oleksii Hrinchuk, Ryan Leary, Boris Ginsburg, Samuel Kriman, Stanislav Beliaev, Vitaly Lavrukhin, Jack Cook, et al. Nemo: a toolkit for building ai applications using neural modules. *arXiv preprint arXiv:1909.09577*, 2019.

Luca Della Libera, Pooneh Mousavi, Salah Zaiem, Cem Subakan, and Mirco Ravanelli. CL-MASR: A continual learning benchmark for multilingual ASR. *CoRR*, abs/2310.16931, 2023. doi: 10.48550/ARXIV.2310.16931. URL https://doi.org/10.48550/arXiv.2310.16931.

Zhiqiu Lin, Jia Shi, Deepak Pathak, and Deva Ramanan. The clear benchmark: Continual learning on real-world imagery. In *Thirty-fifth conference on neural information processing systems datasets and benchmarks track (round 2)*, 2021.

Vincenzo Lomonaco and Davide Maltoni. Core50: a new dataset and benchmark for continuous object recognition. In Sergey Levine, Vincent Vanhoucke, and Ken Goldberg (eds.), *Proceedings of the 1st Annual Conference on Robot Learning*, volume 78 of *Proceedings of Machine Learning Research*, pp. 17–26. PMLR, 13–15 Nov 2017. URL https://proceedings.mlr.press/v78/lomonaco17a.html.

Loren Lugosch, Tatiana Likhomanenko, Gabriel Synnaeve, and Ronan Collobert. Pseudo-labeling for massively multilingual speech recognition. *ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 7687–7691, 2021. URL https://api.semanticscholar.org/CorpusID:240354437.

Arun Mallya and Svetlana Lazebnik. Packnet: Adding multiple tasks to a single network by iterative pruning. In *2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018*, pp. 7765–7773. Computer Vision Foundation / IEEE Computer Society, 2018. doi: 10.1109/CVPR.2018.00810. URL http://openaccess.thecvf.com/content_cvpr_2018/html/Mallya_PackNet_Adding_Multiple_CVPR_2018_paper.html.

Bryan McCann, Nitish Shirish Keskar, Caiming Xiong, and Richard Socher. The natural language decathlon: Multitask learning as question answering. *arXiv preprint arXiv:1806.08730*, 2018.

Andrew C. Morris, Viktoria Maier, and Phil D. Green. From wer and ril to mer and wil: improved evaluation measures for connected speech recognition. In *Interspeech*, 2004. URL https://api.semanticscholar.org/CorpusID:18880375.

Martin Mundt, Yongwon Hong, Iuliia Pliushch, and Visvanathan Ramesh. A wholistic view of continual learning with deep neural networks: Forgotten lessons and the bridge to active and open world learning. *Neural Netw.*, 160(C):306–336, March 2023. ISSN 0893-6080. doi: 10.1016/j.neunet.2023.01.014. URL https://doi.org/10.1016/j.neunet.2023.01.014.

Vahid Noroozi, Somshubra Majumdar, Ankur Kumar, Jagadeesh Balam, and Boris Ginsburg. Stateful conformer with cache-based inference for streaming automatic speech recognition. *ICASSP 2024 - 2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 12041–12045, 2023. URL https://api.semanticscholar.org/CorpusID:266690764.

Kishore Prahallad, Naresh Kumar Elluru, Venkatesh Keri, S. Rajendran, and Alan W. Black. The iiit-h indic speech databases. In *Interspeech*, 2012. URL https://api.semanticscholar.org/CorpusID:10479838.

Vineel Pratap, Qiantong Xu, Anuroop Sriram, Gabriel Synnaeve, and Ronan Collobert. MLS: A large-scale multilingual dataset for speech research. In Helen Meng, Bo Xu, and Thomas Fang Zheng (eds.), *21st Annual Conference of the International Speech Communication Association, Interspeech 2020, Virtual Event, Shanghai, China, October 25-29, 2020*, pp. 2757–2761. ISCA, 2020. doi: 10.21437/INTERSPEECH.2020-2826. URL https://doi.org/10.21437/Interspeech.2020-2826.

Nithya R, Malavika S, Jordan F, Arjun Gangwar, Metilda N J, S Umesh, Rithik Sarab, Akhilesh Kumar Dubey, Govind Divakaran, Samudra Vijaya K, and Suryakanth V Gangashetty. Spring-inx: A multilingual indian language speech corpus by spring lab, iit madras, 2023.

Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. Robust speech recognition via large-scale weak supervision. In *International conference on machine learning*, pp. 28492–28518. PMLR, 2023.

Sylvestre-Alvise Rebuffi, Hakan Bilen, and Andrea Vedaldi. Learning multiple visual domains with residual adapters. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS'17, pp. 506–516, Red Hook, NY, USA, 2017. Curran Associates Inc. ISBN 9781510860964.

David Rolnick, Arun Ahuja, Jonathan Schwarz, Timothy P. Lillicrap, and Gregory Wayne. Experience replay for continual learning. In Hanna M. Wallach, Hugo Larochelle, Alina Beygelzimer, Florence d'Alché-Buc, Emily B. Fox, and Roman Garnett (eds.), *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pp. 348–358, 2019. URL https://proceedings.neurips.cc/paper/2019/hash/fa7cdfad1a5aaf8370ebeda47a1ff1c3-Abstract.html.

Andrei A Rusu, Neil C Rabinowitz, Guillaume Desjardins, Hubert Soyer, James Kirkpatrick, Koray Kavukcuoglu, Razvan Pascanu, and Raia Hadsell. Progressive neural networks. *arXiv preprint arXiv:1606.04671*, 2016.

Samik Sadhu and Hynek Hermansky. Continual learning in automatic speech recognition. In Helen Meng, Bo Xu, and Thomas Fang Zheng (eds.), *Interspeech 2020, 21st Annual Conference of the International Speech Communication Association, Virtual Event, Shanghai, China, 25-29 October 2020*, pp. 1246–1250. ISCA, 2020. doi: 10.21437/INTERSPEECH.2020-2962. URL https://doi.org/10.21437/Interspeech.2020-2962.

Elizabeth Salesky, Matthew Wiesner, Jacob Bremerman, Roldano Cattoni, Matteo Negri, Marco Turchi, Douglas W. Oard, and Matt Post. The multilingual tedx corpus for speech recognition and translation. In Hynek Hermansky, Honza Cernocký, Lukás Burget, Lori Lamel, Odette Scharenborg, and Petr Motlícek (eds.), *22nd Annual Conference of the International Speech Communication Association, Interspeech 2021, Brno, Czechia, August 30 - September 3, 2021*, pp. 3655–3659. ISCA, 2021. doi: 10.21437/INTERSPEECH.2021-11. URL https://doi.org/10.21437/Interspeech.2021-11.

Abhayjeet Singh, Charu Shah, Rajashri Varadaraj, Sonakshi Chauhan, and Prasanta Kumar Ghosh. Spire-sies: A spontaneous indian english speech corpus, 2023.

Brij Mohan Lal Srivastava, Sunayana Sitaram, Rupesh Kumar Mehta, Krishna Doss Mohan, Pallavi Matani, Sandeepkumar Satpal, Kalika Bali, Radhakrishnan Srikanth, and Niranjan Nayak. Interspeech 2018 Low Resource Automatic Speech Recognition Challenge for Indian Languages. In *Proc. 6th Workshop on Spoken Language Technologies for Under-Resourced Languages (SLTU 2018)*, pp. 11–14, 2018. doi: 10.21437/SLTU.2018-3.

Gido M. van de Ven, Tinne Tuytelaars, and Andreas S. Tolias. Three types of incremental learning. *Nat. Mac. Intell.*, 4(12):1185–1197, 2022. doi: 10.1038/S42256-022-00568-3. URL https://doi.org/10.1038/s42256-022-00568-3.

Changhan Wang, Morgane Rivière, Ann Lee, Anne Wu, Chaitanya Talnikar, Daniel Haziza, Mary Williamson, Juan Miguel Pino, and Emmanuel Dupoux. Voxpopuli: A large-scale multilingual speech corpus for representation learning, semi-supervised learning and interpretation. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli (eds.), *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021*, pp. 993–1003. Association for Computational Linguistics, 2021a. doi: 10.18653/V1/2021.ACL-LONG.80. URL https://doi.org/10.18653/v1/2021.acl-long.80.

Changhan Wang, Morgane Rivière, Ann Lee, Anne Wu, Chaitanya Talnikar, Daniel Haziza, Mary Williamson, Juan Miguel Pino, and Emmanuel Dupoux. Voxpopuli: A large-scale multilingual speech corpus for representation learning, semi-supervised learning and interpretation. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli (eds.), *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021*, pp. 993–1003. Association for Computational Linguistics, 2021b.

doi: 10.18653/V1/2021.ACL-LONG.80. URL https://doi.org/10.18653/v1/2021.acl-long.80.

Liyuan Wang, Xingxing Zhang, Hang Su, and Jun Zhu. A comprehensive survey of continual learning: Theory, method and application. *CoRR*, abs/2302.00487, 2023. doi: 10.48550/ARXIV.2302.00487. URL https://doi.org/10.48550/arXiv.2302.00487.

Liyuan Wang, Xingxing Zhang, Hang Su, and Jun Zhu. A comprehensive survey of continual learning: theory, method and application. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2024.

Yifan Yang, Zheshu Song, Jianheng Zhuo, Mingyu Cui, Jinpeng Li, Bo Yang, Yexing Du, Ziyang Ma, Xunying Liu, Ziyuan Wang, Ke Li, Shuai Fan, Kai Yu, Wei-Qiang Zhang, Guoguo Chen, and Xie Chen. Gigaspeech 2: An evolving, large-scale and multi-domain ASR corpus for low-resource languages with automated crawling, transcription and refinement. *CoRR*, abs/2406.11546, 2024a. doi: 10.48550/ARXIV.2406.11546. URL https://doi.org/10.48550/arXiv.2406.11546.

Yifan Yang, Zheshu Song, Jianheng Zhuo, Mingyu Cui, Jinpeng Li, Bo Yang, Yexing Du, Ziyang Ma, Xunying Liu, Ziyuan Wang, et al. Gigaspeech 2: An evolving, large-scale and multi-domain asr corpus for low-resource languages with automated crawling, transcription and refinement. *arXiv preprint arXiv:2406.11546*, 2024b.

Friedemann Zenke, Ben Poole, and Surya Ganguli. Continual learning through synaptic intelligence. In *Proceedings of the 34th International Conference on Machine Learning - Volume 70*, ICML'17, pp. 3987–3995. JMLR.org, 2017.

Kevin Zhang, Luka Chkhetiani, Francis McCann Ramirez, Yash Khare, Andrea Vanzo, Michael Liang, Sergio Ramirez Martin, Gabriel Oexle, Ruben Bousbib, Taufiquzzaman Peyash, et al. Conformer-1: Robust asr via large-scale semisupervised bootstrapping. *arXiv preprint arXiv:2404.07341*, 2024.

Yu Zhang, Wei Han, James Qin, Yongqiang Wang, Ankur Bapna, Zhehuai Chen, Nanxin Chen, Bo Li, Vera Axelrod, Gary Wang, Zhong Meng, Ke Hu, Andrew Rosenberg, Rohit Prabhavalkar, Daniel S. Park, Parisa Haghani, Jason Riesa, Ginger Perng, Hagen Soltau, Trevor Strohman, Bhuvana Ramabhadran, Tara Sainath, Pedro Moreno, Chung-Cheng Chiu, Johan Schalkwyk, Françoise Beaufays, and Yonghui Wu. Google usm: Scaling automatic speech recognition beyond 100 languages, 2023.

Fan Zhou and Chengtai Cao. Overcoming catastrophic forgetting in graph neural networks with experience replay. In *Thirty-Fifth AAAI Conference on Artificial Intelligence, AAAI 2021, Thirty-Third Conference on Innovative Applications of Artificial Intelligence, IAAI 2021, The Eleventh Symposium on Educational Advances in Artificial Intelligence, EAAI 2021, Virtual Event, February 2-9, 2021*, pp. 4714–4722. AAAI Press, 2021. doi: 10.1609/AAAI.V35I5.16602. URL https://doi.org/10.1609/aaai.v35i5.16602.

A APPENDIX

Table 3 presents a comparative overview of relevant datasets that can be used in LIL, DIL and LIDIL scenarios.

Table 3: Table comparing different publicly available dataset and their usability in different CL scenarios.

Dataset	#Langs	#Domains (present in Metadata)	# Hours	Audio Source	Transcription	Supported scenario		
						LIL	DIL	LIDIL
LibriSpeech (lib, 2015)	1	-	1000	Audiobooks	Force Aligned	✗	✗	✗
GigaSpeech (Harte et al., 2023)	1	23	10000	YouTube	Force Aligned	✗	✓	✗
VoxPopuli(Wang et al., 2021a)	16	-	1800	Parliament Recordings	Force Aligned	✓	✗	✗
TED-LIUM(Hernandez et al., 2018)	1	-	452	TED talks	Force Aligned	✗	✗	✗
Spoken Wikipedia (Baumann et al., 2019)	3	-	1005	Crowdsourcing	Force Aligned	✓	✗	✗
Multilingual TEDx (Salesky et al., 2021)	8	-	765	TED Talks	Force Aligned	✓	✗	✗
Multilingual LibriSpeech (Pratap et al., 2020)	8	-	44500	Audiobooks	Force Aligned	✓	✗	✗
GigaSpeech 2 (Yang et al., 2024a)	3	-	22015	YouTube	Pseudolabelled	✓	✗	✗
Switchboard Corpus [2]	1	-	260	Human	Manual	✗	✗	✗
Common Voice 19 (Ardila et al., 2020)	131	-	21594	Human	Manual	✓	✗	✗
FLEURS (Conneau et al., 2022)	102	-	1400	Human	Manual	✓	✗	✗
MSR Srivastava et al., 2018	3	-	150	Human	Manual	✓	✗	✗
OpenSLR Kjartansson et al., 2018	6	-	1247	Human	Manual	✓	✗	✗
Crowdsourced Multispeaker Speech Dataset (He et al., 2020)	6	-	35	Human	Manual	✓	✗	✗
MUCS (Diwan et al., 2021)	3	-	350	Human	Manual	✓	✗	✗
IndicSUPERB (Javed et al., 2023a)	12	-	1684	Human	Manual	✓	✗	✗
Shrutilipi (Bhogale et al., 2023a)	12	-	6457	Newsonair	Force Aligned	✓	✗	✗
Graamvaani Bhanushali et al. (2022)	1	-	108	Human	Manual	✗	✗	✗
IIIS-Mile A et al. (2022a;b)	2	-	500	Human	Manual	✓	✗	✗
Kashmiri Data Corpus[3]	1	-	1	Human	Manual	✗	✗	✗
Vāksañcayah (Adiga et al., 2021)	1	-	78	Human	Manual	✗	✗	✗
The IIIT-H Indic Speech Databases (Prahallad et al., 2012)	7	-	11	Human	Manual	✓	✗	✗
Microsoft-IITB Marathi Speech Corpus (Abraham et al., 2020)	1	-	109	Human	Manual	✗	✗	✗
SMC Malayalam Speech Corpus [4]	1	4	2	Human	Manual	✗	✓	✗
IITM ASR Challange [5]	3	-	690	YouTube	Force Aligned	✓	✗	✗
NPTEL (Bhogale et al., 2023b)	8	-	6400	YouTube	Force Aligned	✓	✗	✗
IndicTTS (ind, 2016)	13	-	225	Human	Manual	✓	✗	✗
Svarah (Javed et al., 2023b)	1	37	10	Human	Manual	✗	✓	✗
SPRING-INX (R et al., 2023)	10	-	3302	Human	Manual	✓	✗	✗
SPIRE-SIES (Singh et al., 2023)	1	13	23	Human	Pseudolabelled	✗	✓	✗
Lahaja (Javed et al., 2024a)	1	83	12.5	Human	Manual	✗	✓	✗
Nirantar	22	208	3250	Human	Manual	✓	✓	✓

[2]https://catalog.ldc.upenn.edu/LDC97S62
[3]https://openslr.org/122/
[4]https://blog.smc.org.in/malayalam-speech-corpus/
[5]https://sites.google.com/view/indian-language-asrchallenge/home

Figures 7 to 9 present the results for the original episodic sequence (Random Order 1) and two additional randomized sequences (Random Order 2 and Random Order 3) in the LIDIL scenario. The following lines list the original task order and two more permutations of it for the LIDIL scenario.

- Random Order 1: 0→1→2→3→4→5→6→7→8→9→10→11
- Random Order 2: 0→11→1→2→10→8→5→9→3→4→6→7
- Random Order 3: 0→8→6→7→9→4→5→1→2→3→11→10

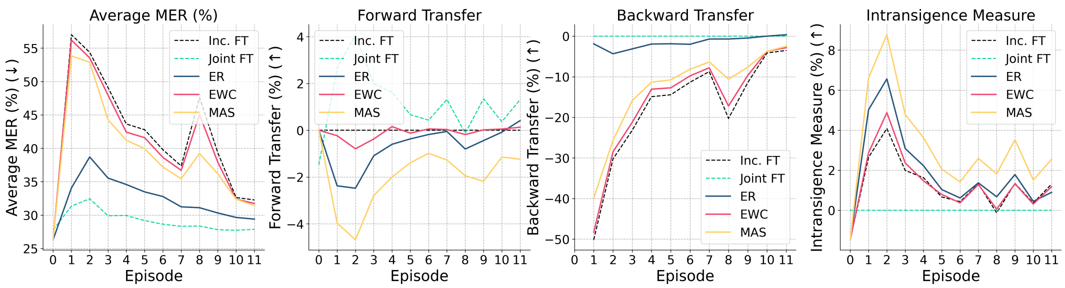


Figure 7: Random Order 1 for LIDIL Scenario.

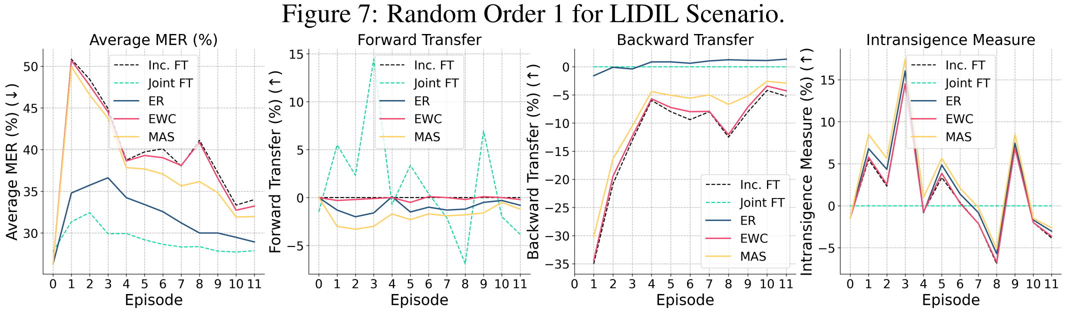


Figure 8: Random Order 2 for LIDIL Scenario.

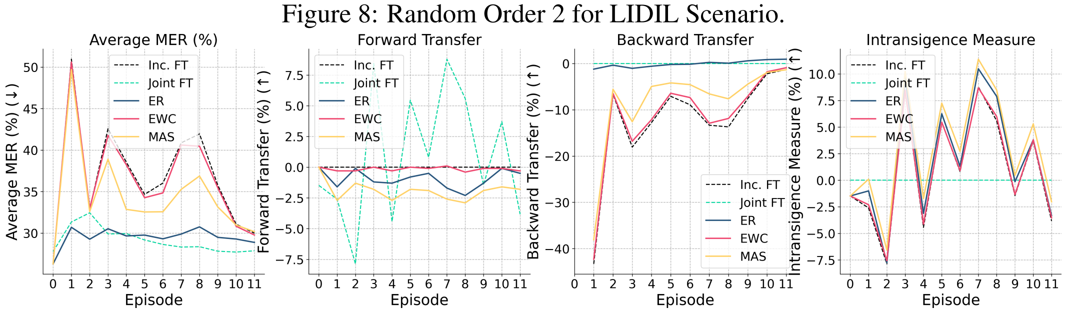


Figure 9: Random Order 3 for LIDIL Scenario

Figure 10 present the results LIL scenario involving adapters.

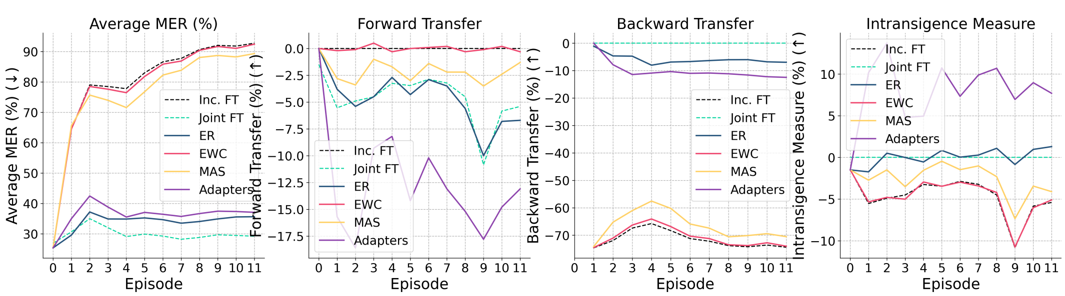


Figure 10: Results on LIL scenario using different CL methods, including adapters.

Figures 11 to 13 show the cross-lingual transfer of information for two language families, Indo-Aryan and Dravidian, in the LIDIL setting.

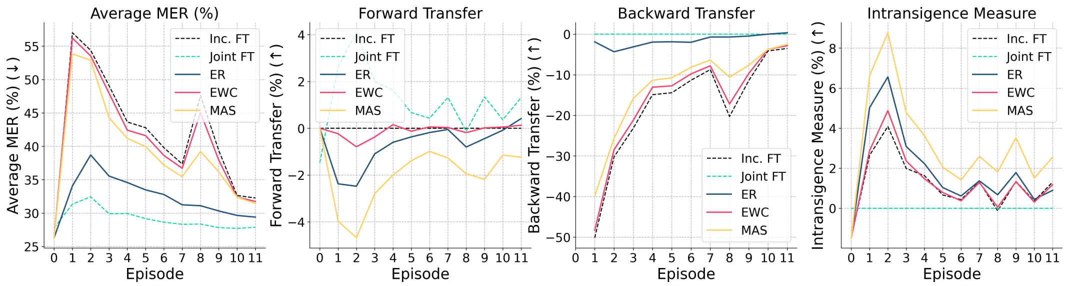


Figure 11: Comparison of different CL approaches for LIDIL scenario

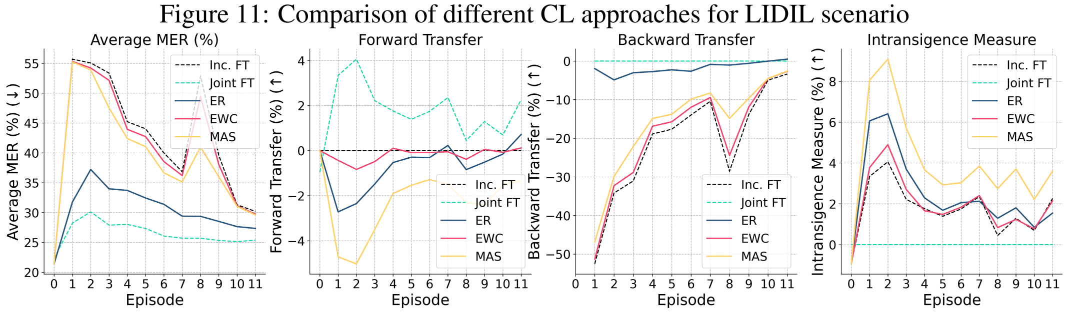


Figure 12: Comparison of different CL approaches for LIDIL scenario for IndoAryan language family splice.

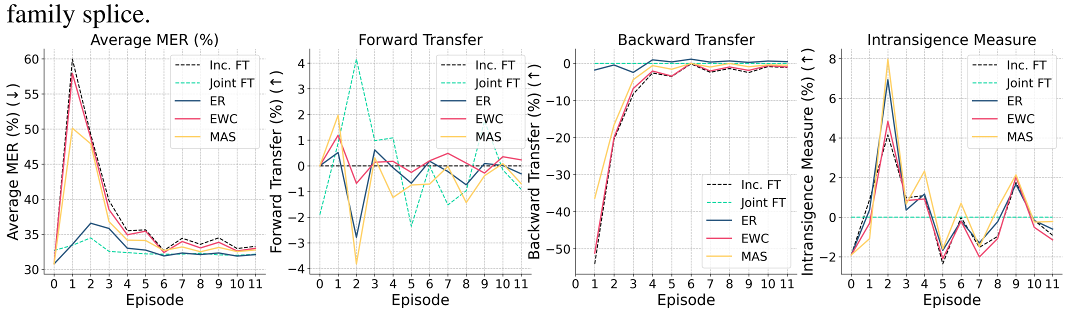


Figure 13: Comparison of different CL approaches for LIDIL scenario for Dravidian language family splice.

Figures 14 to 15 illustrate how the domains and vocabulary evolve over episodes.

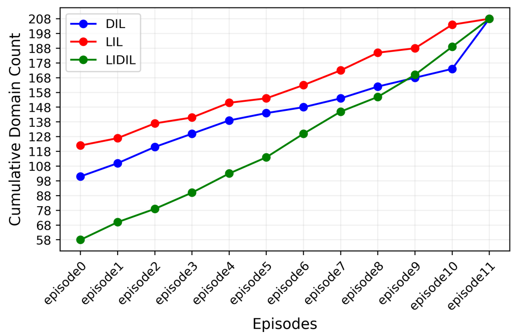
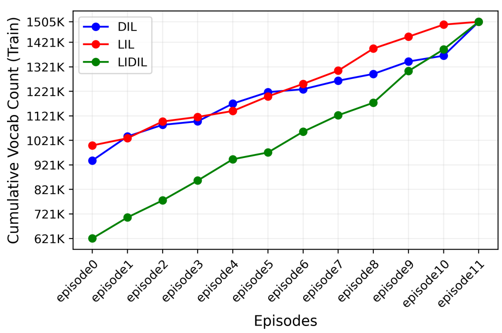
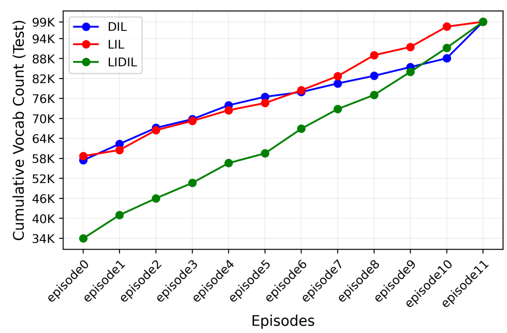


Figure 14: Figure showing the cumulative improvement of domains across episodes.



(a) Training set.



(b) Test set.

Figure 15: Comparison of cumulative vocabulary improvement across episodes for training and test sets.

Table 4: Table comparing different publicly available dataset and their usability in different CL scenarios

Language Code	Domain/ District	Train (hours)	Test (minutes)	WER (on Test)	Episodic presence		
					LIL	DIL	LIDIL
as	Barpeta	12	15.1	22.3%	episode0	episode0	episode0
as	Biswanath	18	15.1	16.3%	episode0	episode0	episode10
as	Charaideo	7.7	15.0	18.9%	episode0	episode0	episode9
as	Darrang	14.3	15.1	24.4%	episode0	episode3	episode6
as	Dhemaji	19.4	15.1	17.6%	episode0	episode8	episode10
as	Dibrugarh	17.6	15.0	19.1%	episode0	episode2	episode10
as	Kamrup Metropolitan	21.8	15.0	21.8%	episode0	episode11	episode0
as	Lakhimpur	38.6	15.0	22.1%	episode0	episode11	episode0
as	Morigaon	20.3	15.2	25.6%	episode0	episode0	episode0
as	Nagaon	18.7	15.1	23.3%	episode0	episode0	episode0
as	Nalbari	24.9	15.0	25.5%	episode0	episode4	episode0
as	Sivasagar	0.6	5.8	18.5%	episode0	episode0	episode0
as	Sonitpur	17.6	15.1	17.6%	episode0	episode0	episode3
as	Tinsukia	5.3	15.0	18.2%	episode0	episode6	episode6
bn	Jalpaiguri	0.8	15.1	18.8%	episode0	episode11	episode7
bn	Jhargram	28.9	15.1	15.2%	episode0	episode0	episode11
bn	Nadia	24.1	15.0	17.7%	episode0	episode11	episode0
bn	North 24 Parganas	2.9	15.1	13.5%	episode0	episode9	episode0
bn	Paschim Bardhaman	31.7	15.0	15.7%	episode0	episode11	episode6
bn	Paschim Medinipur	29.8	15.0	16.6%	episode0	episode7	episode0
bn	Purba Bardhaman	24.7	15.0	17.9%	episode0	episode0	episode0
bn	Purba Medinipur	23.2	15.0	17.7%	episode0	episode0	episode5
bn	Purulia	19.5	15.2	16.6%	episode0	episode0	episode7
bn	South 24 Parganas	18.7	15.0	17.8%	episode0	episode0	episode4
brx	Baksa	51.3	15.1	26.3%	episode0	episode9	episode0
brx	Chirang	106.2	15.1	28.2%	episode0	episode0	episode11
brx	Kokrajhar	81.3	15.1	29.0%	episode0	episode5	episode0
brx	Udalguri	46.2	15.0	30.8%	episode0	episode0	episode6
hi	Darbhanga	3.4	15.1	13.5%	episode0	episode0	episode0
hi	Balaghat	7.6	15.1	16.7%	episode0	episode0	episode0
hi	Bhopal	26.9	15.2	12.6%	episode0	episode0	episode7
hi	Gwalior	2.2	15.0	15.2%	episode0	episode3	episode5
hi	Jabalpur	2.2	15.2	16.9%	episode0	episode0	episode11
hi	Katni	1.6	15.0	15.2%	episode0	episode0	episode10
hi	Jaipur	27.3	15.1	16.3%	episode0	episode0	episode1
hi	Jodhpur	25.2	15.1	17.4%	episode0	episode4	episode0
hi	Karauli	10.2	15.1	16.4%	episode0	episode8	episode6
hi	Bhadohi	2.2	15.1	17.0%	episode0	episode11	episode0
hi	Mirzapur	4.9	15.0	18.0%	episode0	episode11	episode0
hi	Sonbhadra	20.7	15.1	16.8%	episode0	episode8	episode0
mai	Darbhanga	34.6	15.0	30.7%	episode0	episode11	episode2
mai	Begusarai	0.3	5.5	32.5%	episode0	episode11	episode4
mai	Madhubani	33.3	15.0	32.0%	episode0	episode2	episode0
mai	Muzaffarpur	26.8	15.1	32.7%	episode0	episode0	episode5
mai	Purnia	40.9	15.1	41.0%	episode0	episode0	episode0
mai	Saharsa	26.8	15.2	32.3%	episode0	episode4	episode4
mai	Samastipur	7.3	15.0	40.4%	episode0	episode11	episode0
mai	Sitamarhi	32.7	15.4	38.8%	episode0	episode0	episode8
mai	Supaul	39.9	15.0	35.7%	episode0	episode0	episode0
ml	Ernakulam	0.1	11.7	32.3%	episode0	episode10	episode10
ml	Kannur	14.4	15.2	41.6%	episode0	episode0	episode0
ml	Kasaragod	11	15.0	36.4%	episode0	episode0	episode6
ml	Kottayam	12.4	15.1	39.4%	episode0	episode0	episode0
ml	Kozhikode	40.1	15.1	37.4%	episode0	episode1	episode0
ml	Malappuram	1.2	15.1	34.2%	episode0	episode2	episode1
ml	Palakkad	45.5	15.1	39.3%	episode0	episode0	episode10

Continued on next page

Language Code	Domain/ District	Train (hours)	Test (minutes)	WER (on Test)	Episodic presence		
					LIL	DIL	LIDIL
ml	Thiruvananthapuram	6.9	15.0	37.8%	episode0	episode0	episode6
ml	Thrissur	1.8	3.9	39.6%	episode0	episode3	episode0
ml	Wayanad	32.5	15.2	44.8%	episode0	episode9	episode0
ne	Jalpaiguri	22.5	15.2	20.6%	episode0	episode0	episode0
ne	Alipurduar	1.3	15.1	25.8%	episode0	episode2	episode0
ne	Darjeeling	109.8	15.1	17.1%	episode0	episode0	episode9
ne	Kalimpong	113.3	15.0	17.0%	episode0	episode1	episode3
pa	Fatehgarh Sahib	27.8	15.0	15.2%	episode0	episode8	episode0
pa	Mohali	34.5	15.0	11.7%	episode0	episode0	episode0
pa	Patiala	1.5	15.1	17.0%	episode0	episode0	episode11
pa	Rupnagar	30.5	15.0	13.5%	episode0	episode7	episode6
pa	Shaheed Bhagat Singh Nagar	27.5	15.0	12.3%	episode0	episode7	episode9
sat	Jhargram	22	15.1	29.2%	episode0	episode11	episode0
sat	Paschim Bardhaman	26.4	15.1	31.4%	episode0	episode11	episode10
sat	Purba Bardhaman	21.7	15.1	35.3%	episode0	episode0	episode0
sat	Purulia	6.3	15.0	46.7%	episode0	episode11	episode1
sat	Bankura	33.8	15.1	34.3%	episode0	episode0	episode7
sat	Birbhum	45.7	15.0	40.3%	episode0	episode0	episode0
sat	Malda	1.4	15.0	40.4%	episode0	episode0	episode6
sat	Uttar Dinajpur	2.9	15.0	47.6%	episode0	episode11	episode0
ta	Ariyalur	4.4	15.1	29.0%	episode0	episode3	episode11
ta	Coimbatore	12.9	15.1	36.3%	episode0	episode11	episode8
ta	Cuddalore	11.7	15.0	31.4%	episode0	episode1	episode0
ta	Dharmapuri	12.1	15.0	34.7%	episode0	episode0	episode6
ta	Erode	15.3	15.1	33.9%	episode0	episode0	episode0
ta	Kallakurichi	16	15.0	32.0%	episode0	episode0	episode7
ta	Krishnagiri	13.8	15.0	32.6%	episode0	episode0	episode0
ta	Mayiladuthurai	32.2	15.1	34.9%	episode0	episode11	episode2
ta	Nagapattinam	20.4	15.1	37.1%	episode0	episode0	episode0
ta	Namakkal	21	15.1	37.1%	episode0	episode0	episode0
ta	Perambalur	2.6	15.1	37.1%	episode0	episode10	episode4
ta	Pudukkottai	6	15.1	26.4%	episode0	episode4	episode0
ta	Salem	10.8	15.0	33.7%	episode0	episode0	episode6
ta	Sivaganga	15.1	15.1	35.2%	episode0	episode8	episode0
ta	Thanjavur	1.3	15.0	36.5%	episode0	episode11	episode0
ta	Tiruchirappalli	3.1	15.1	38.4%	episode0	episode5	episode11
ta	Tiruppur	11.6	15.0	35.9%	episode0	episode0	episode11
ta	Tiruvarur	16.6	15.1	29.9%	episode0	episode10	episode11
ta	Viluppuram	5.8	15.1	27.7%	episode0	episode0	episode0
te	Anakapalli	1.1	15.3	20.0%	episode0	episode11	episode10
te	Chittoor	19.1	15.1	26.6%	episode0	episode0	episode0
te	East Godavari	14.9	15.1	28.1%	episode0	episode11	episode5
te	Eluru	10.6	15.1	21.4%	episode0	episode0	episode0
te	Guntur	8.3	15.1	20.7%	episode0	episode1	episode4
te	Kakinada	15.9	15.0	29.8%	episode0	episode4	episode0
te	Konaseema	12.8	15.0	16.9%	episode0	episode6	episode0
te	Krishna	2.1	3.2	23.1%	episode0	episode0	episode0
te	N T Rama Rao	4.3	15.3	27.8%	episode0	episode3	episode10
te	Nellore	5.6	15.1	34.3%	episode0	episode2	episode7
te	Palnadu	8.2	15.1	21.3%	episode0	episode0	episode0
te	Sri Balaji	18.7	15.1	32.0%	episode0	episode4	episode0
te	Srikakulam	10.8	15.0	29.6%	episode0	episode0	episode5
te	Visakhapatnam	2.3	15.1	29.8%	episode0	episode0	episode0
te	Vizianagaram	9.9	15.0	30.3%	episode0	episode4	episode3
te	West Godavari	4.7	15.2	24.7%	episode0	episode9	episode4
te	Hyderabad	16.7	15.0	31.3%	episode0	episode0	episode4
te	Karimnagar	0	1.6	7.8%	episode0	episode8	episode0
te	Mahbubnagar	1.1	15.2	21.4%	episode0	episode3	episode3
te	Mancherial	4.5	15.2	30.1%	episode0	episode0	episode8
te	Medchal	4.3	15.1	27.0%	episode0	episode0	episode7

Continued on next page

Language Code	Domain/ District	Train (hours)	Test (minutes)	WER (on Test)	Episodic presence		
					LIL	DIL	LIDIL
te	Nalgonda	7.5	15.1	29.8%	episode0	episode0	episode0
te	Nirmal	2.1	15.1	29.0%	episode0	episode3	episode0
te	Ranga Reddy	12.9	15.1	32.0%	episode0	episode11	episode9
te	Sangareddy	4.1	15.0	24.0%	episode0	episode0	episode0
te	Vikarabad	7.1	15.1	26.6%	episode0	episode0	episode0
te	Yadadri Bhuvanagiri	2.7	15.0	19.1%	episode0	episode0	episode6
doi	Jammu	12.2	15.1	30.4%	episode1	episode3	episode2
doi	Kathua	0.3	13.4	17.9%	episode1	episode7	episode7
doi	Reasi	55.1	15.2	30.1%	episode1	episode0	episode11
doi	Samba	0.8	4.9	22.4%	episode1	episode0	episode7
doi	Udhampur	45	15.0	35.6%	episode1	episode1	episode2
sa	Chittoor	3.9	15.1	19.6%	episode10	episode11	episode3
sa	Bagalkot	2	15.0	22.9%	episode10	episode0	episode10
sa	Bangalore Rural	0.6	15.1	21.4%	episode10	episode10	episode11
sa	Bangalore Urban	6.1	15.1	20.8%	episode10	episode11	episode5
sa	Chikkamagaluru	2.6	15.0	23.2%	episode10	episode0	episode2
sa	Dakshina Kannada	12.2	15.1	21.9%	episode10	episode0	episode3
sa	Mysore	3.8	15.0	17.3%	episode10	episode11	episode8
sa	Shimoga	4.3	15.1	20.3%	episode10	episode0	episode1
sa	Udupi	8.3	15.3	23.5%	episode10	episode0	episode9
sa	Uttara Kannada	11.4	15.1	22.3%	episode10	episode0	episode3
sa	Nagpur	0.6	15.1	17.4%	episode10	episode11	episode9
sa	Jaipur	2.6	15.2	24.7%	episode10	episode11	episode2
sa	Coimbatore	1.6	6.3	34.0%	episode10	episode0	episode1
sa	Chennai	3.3	15.1	24.0%	episode10	episode9	episode5
sa	Hyderabad	1.5	15.0	21.5%	episode10	episode11	episode6
sa	Ranga Reddy	0	15.0	21.7%	episode10	episode0	episode5
sd	South Delhi	0.1	2.0	21.6%	episode11	episode0	episode5
sd	Surat	2	15.0	20.0%	episode11	episode2	episode3
sd	Mumbai Suburban	3.5	15.0	20.8%	episode11	episode0	episode7
sd	Thane	20.5	15.1	23.2%	episode11	episode2	episode1
ks	Anantnag	11.2	15.1	43.5%	episode2	episode0	episode1
ks	Bandipora	3.7	15.2	30.8%	episode2	episode0	episode2
ks	Baramulla	11	15.1	45.8%	episode2	episode0	episode7
ks	Budgam	7.7	15.0	38.7%	episode2	episode0	episode11
ks	Ganderbal	16.5	15.1	34.8%	episode2	episode0	episode10
ks	Kulgam	16.2	15.0	45.6%	episode2	episode7	episode1
ks	Kupwara	11.8	15.1	42.7%	episode2	episode6	episode11
ks	Pulwama	2.5	15.2	36.4%	episode2	episode1	episode1
ks	Shopian	19.6	15.1	37.7%	episode2	episode9	episode11
ks	Srinagar	3.2	15.0	41.0%	episode2	episode2	episode4
gu	Ahmedabad	4.8	15.2	14.6%	episode3	episode5	episode9
gu	Aravalli	2.6	15.0	24.5%	episode3	episode0	episode11
gu	Mehsana	4.8	15.0	16.7%	episode3	episode0	episode6
gu	Morbi	6.9	15.2	20.4%	episode3	episode4	episode7
ur	South Delhi	12.4	15.0	13.1%	episode4	episode11	episode6
ur	Central Delhi	17	15.2	15.9%	episode4	episode0	episode10
ur	Nashik	14.1	15.0	13.6%	episode4	episode0	episode10
ur	Hyderabad	12.1	15.1	15.3%	episode4	episode11	episode7
ur	Aligarh	16.6	15.1	13.3%	episode4	episode0	episode7
ur	Gautam Buddha Nagar	18.5	15.2	13.4%	episode4	episode8	episode4
ur	Ghaziabad	2.6	14.3	19.2%	episode4	episode0	episode10
ur	Lucknow	18.2	15.1	14.1%	episode4	episode0	episode3
ur	Mau	3.6	15.1	13.8%	episode4	episode5	episode8
ur	Shahjahanpur	5.8	15.1	10.8%	episode4	episode6	episode11
kok	Bardez	33.1	15.1	32.3%	episode5	episode0	episode11
kok	Canacona	46.2	15.0	32.7%	episode5	episode0	episode9
kok	Tiswadi	20.3	15.1	27.9%	episode5	episode7	episode10
or	Bhadrak	2.2	15.0	18.6%	episode6	episode0	episode11
or	Boudh	12.5	15.0	28.8%	episode6	episode11	episode1

Continued on next page

Language Code	Domain/ District	Train (hours)	Test (minutes)	WER (on Test)	Episodic presence		
					LIL	DIL	LIDIL
or	Cuttack	0	0.7	37.5%	episode6	episode3	episode8
or	Dhenkanal	20.8	15.3	23.7%	episode6	episode0	episode10
or	Jajpur	15.3	15.1	22.0%	episode6	episode0	episode8
or	Kalahandi	0	1.2	42.9%	episode6	episode11	episode1
or	Kandhamal	21.6	15.1	21.3%	episode6	episode0	episode9
or	Khordha	26.4	15.1	21.0%	episode6	episode11	episode8
or	Nayagarh	22.3	15.0	22.9%	episode6	episode2	episode9
mr	Nagpur	15	15.0	18.9%	episode7	episode0	episode11
mr	Thane	4.3	15.1	16.5%	episode7	episode2	episode10
mr	Akola	24.9	15.2	17.1%	episode7	episode10	episode9
mr	Amravati	16.2	15.1	18.7%	episode7	episode11	episode1
mr	Buldhana	18.9	15.0	17.6%	episode7	episode0	episode9
mr	Raigad	0.6	6.8	18.0%	episode7	episode0	episode5
mr	Solapur	1.4	2.1	16.8%	episode7	episode0	episode4
mr	Wardha	2.5	15.1	16.4%	episode7	episode1	episode3
mr	Washim	7.5	15.1	22.3%	episode7	episode0	episode9
mr	Yavatmal	23.9	15.1	16.2%	episode7	episode2	episode9
kn	Bangalore Rural	5.7	15.0	34.2%	episode8	episode10	episode2
kn	Bangalore Urban	4	15.1	30.4%	episode8	episode0	episode8
kn	Mysore	1.2	2.1	43.6%	episode8	episode0	episode5
kn	Shimoga	17.6	15.0	22.2%	episode8	episode11	episode4
kn	Udupi	1.6	13.4	29.2%	episode8	episode0	episode2
kn	Bidar	8.1	15.0	43.6%	episode8	episode1	episode4
kn	Chamarajanagar	1.5	1.3	29.2%	episode8	episode0	episode3
kn	Chikkaballapur	8.3	15.1	22.2%	episode8	episode8	episode6
kn	Chitradurga	10.9	15.0	29.1%	episode8	episode5	episode11
kn	Davanagere	8.9	15.1	30.6%	episode8	episode0	episode10
kn	Kolar	14	15.2	23.8%	episode8	episode0	episode8
kn	Tumkur	11.4	15.0	26.9%	episode8	episode1	episode9
mni	Imphal West	18.6	15.1	21.6%	episode9	episode4	episode7
mni	Kakching	3.7	15.0	37.3%	episode9	episode0	episode10
mni	Thoubal	18.3	15.1	21.8%	episode9	episode11	episode4