ESB: A Benchmark For Multi-Domain End-to-End Speech Recognition

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Abstract

Speech recognition applications cover a range of different audio and text distributions, with different speaking styles, background noise, transcription punctuation and character casing. However, many speech recognition systems require dataset-specific tuning (audio filtering, punctuation removal and normalisation of casing), therefore assuming a-priori knowledge of both the audio and text distributions. This tuning requirement can lead to systems failing to generalise to other datasets and domains. To promote the development of multi-domain speech systems, we introduce the End-to-end Speech Benchmark (ESB) for evaluating the performance of a single automatic speech recognition (ASR) system across a broad set of speech datasets. Benchmarked systems must use the same data pre- and post-processing algorithm across datasets - assuming the audio and text data distributions are a-priori unknown. We compare a series of state-of-the-art (SoTA) end-to-end (E2E) systems on this benchmark, demonstrating how a single speech system can be applied and evaluated on a wide range of data distributions. We find E2E systems to be effective across datasets: in a fair comparison, E2E systems achieve within 2.6% of SoTA systems tuned to a specific dataset. Our analysis reveals that transcription artefacts, such as punctuation and casing, pose difficulties for ASR systems and should be included in evaluation. We believe E2E benchmarking over a range of datasets promotes the research of multi-domain speech recognition systems. ESB is available at https://huggingface.co/esb

1 Introduction

Speech recognition covers various applications, including dictation, voice assistants, video captioning, telephone conversations and meeting transcriptions (Aksenova et al., 2021). Each application has domain-specific data distributions for both the audio inputs and transcription outputs. The audio inputs are derived from different recording conditions, degrees of background noise, speakers and styles (narrated, oratory or spontaneous). The nature of the transcriptions is also domain-dependent; in formal settings, such as meeting transcriptions, the text must be orthographic and satisfy standard formatting conventions. Whereas in more informal settings, such as telephone conversations, punctuation and casing are often omitted (Kim & Woodland, 2003). To handle the diversity of speech recognition conditions, there is a need for multi-domain systems that maintain their performance over a collection of datasets with different audio and transcription distributions.

However, most automatic speech recognition (ASR) systems are trained and evaluated on a single dataset, utilising dataset-specific model architectures and pre-/post-processing to optimise for single dataset performance (Likhomanenko et al., 2020). Such dataset-specific tuning assumes a-priori knowledge of both the audio and text distribution and yields systems that transfer poorly to other datasets and domains. A generalisable system should transfer to different datasets and domains with training data, but without the need for dataset-specific tuning (Wang et al., 2019b) or a-priori knowledge of the data distributions. End-to-end (E2E) systems consist of a single model that maps the raw audio inputs to the transcription outputs (Graves & Jaitly, 2014). Learning directly from data, E2E systems do not require dataset-specific configurations (Hannun et al., 2014). As such,

\footnote{orthographic: the accepted way of spelling and writing words according to standard usage (McIntosh & Cambridge University Press, 2015).}
they can be applied independently to different datasets and domains (Chan et al., 2021; Radford et al., 2022).

To facilitate the research of multi-domain, generalisable ASR systems, we present the End-to-end Speech Benchmark (ESB), a benchmark for evaluating a single ASR system across a collection of speech datasets spanning different domains and speech recognition conditions. Benchmarked systems must use the same architecture across datasets and may not use dataset-specific pre- or post-processing. Therefore, ESB favours systems that can be applied independently across speech recognition domains with no a-priori knowledge of the data distributions. None of the datasets presented in ESB were created specifically for the benchmark; all datasets are pre-existing for the reason that they are widely considered by the speech community to be the most applicable, challenging and interesting datasets. We adopt an open-source and open-science approach by considering datasets that are freely available and accessible.

To demonstrate ESB, we perform baseline experiments with five different E2E approaches. We find these E2E systems to be effective across datasets. In a fair comparison, they perform to within 2.6% word error rate of state-of-the-art systems tuned to a specific dataset. Our analysis shows that transcription artefacts, such as punctuation and casing, make the task of speech recognition more difficult and should be included in evaluation. We believe E2E benchmarking over a range of datasets encourages the research of multi-domain speech recognition systems.

2 RELATED WORK

Speech recognition datasets have long focused on covering different domains and speaking styles: the TIMIT (Garofolo et al., 1993a) and Wall-Street Journal (Garofolo et al., 1993b) corpora contain news broadcast recordings, SwitchBoard (Godfrey et al., 1992) and Fisher (Cieri et al., 2004a;b, 2005a;b) spontaneous telephone conversations, LibriSpeech (Panayotov et al., 2015) narrated audiobooks, Common Voice (Ardila et al., 2020) narrated Wikipedia articles and TED-LIUM (Hernandez et al., 2018) oratory educational talks. More recently, datasets such as People’s Speech (Galvez et al., 2021) and GigaSpeech (Chen et al., 2021) extend this to cover multiple domains in one dataset. However, these datasets lack certain important domains and speaking styles, such as conversational speech, which are currently only covered by certain individual datasets. We see this as an important trend towards multi-domain speech recognition and collect different datasets to form a unified ASR benchmark.

Traditionally, ASR systems are trained on case and punctuation normalised text (NIST, 1998; Povey et al., 2011); the transcriptions are pre-processed to remove casing and punctuation before training and evaluation. However, in certain speech recognition applications, orthographic transcriptions are required (Kim & Woodland, 2001). Recent work has looked at training ASR systems on orthographic transcriptions (O’Neill et al., 2021; Radford et al., 2022), relying on a data-driven E2E approach in learning to predict cased and punctuated outputs. However, the features of orthographic text remain challenging for ASR systems. We evaluate a single system over multiple datasets and include all dataset-specific transcription formatting requirements.

For text understanding, GLUE (Wang et al., 2019b) and SuperGLUE (Wang et al., 2019a) provide well established benchmarks for assessing the generalisation abilities of a single system over a range of different natural language understanding tasks. The SUPERB (Yen Yang et al., 2021) and XTREME-S (Conneau et al., 2022) benchmarks assess a single system over a multiple spoken language processing tasks. This paper extends these efforts to show that English ASR has sufficient diversity in datasets and domains to merit a benchmark of its own.

3 MOTIVATION FOR AN END-TO-END BENCHMARK

Different speech domains have different data distributions for audio artefacts (quality, speakers and styles) and transcription outputs (punctuation, casing, orthography). In using the term end-to-end (E2E), we refer to systems that map from the raw audio inputs to the transcription outputs without domain-specific architectures or additional processing. In this section, we describe the existing works regarding multi-domain and E2E ASR and outline the principal issues involved.
Recent datasets have focused on domains with more challenging audio inputs, specifically in audio quality, speakers and speaking style (Panayotov et al., 2015; Ardila et al., 2020; Wang et al., 2021; Hernandez et al., 2018; Chen et al., 2021; O’Neill et al., 2021; Del Rio et al., 2022; Carletta, 2007; Renals et al., 2007; Godfrey et al., 1992; Cieri et al., 2004a;b; 2005a;b). These datasets incorporate distinct audio domains, each with different recording conditions and degrees of background noise. Each dataset includes speakers from both native or non-native English speaking backgrounds, and together cover accents and dialects from seven different language regions (Del Rio et al., 2022). The speaking style for each dataset falls into one of three categories: narrated, oratory or spontaneous, with each style having different distributions for speaking speed and utterance length. We discuss the individual datasets in detail in Section 4.

For many ASR systems, a series of dataset specific pre- and post-processing steps are applied when training and evaluating systems on individual datasets. For the 10 datasets in this work, there are 10 different Kaldi (Povey et al., 2011) recipes in use, each with unique pre- and post-processing steps. Of these recipes, one is not even publicly accessible. Employing dataset-specific pre-processing steps results in systems that do not transfer to different domains. For example, a system that extracts speech features without a noise-suppression algorithm works adequately well for a dataset with low-background noise, but the same approach produces much worse results on a noisy dataset (Kim & Stern, 2016).

Recent speech recognition datasets also include full transcriptions with all the necessary orthographic features required for their respective domains (Carletta, 2007; Renals et al., 2007; O’Neill et al., 2021; Del Rio et al., 2022). These datasets aim to encourage ASR systems capable of producing transcriptions that adhere to the formatting requirements of the target text domain. We note that this differs from the standard ASR output transcription format known as Standard Normalised Orthographic Representation (SNOR) (NIST, 1998), which consists of single-case letters without punctuation marks or numbers. This format is necessary for ASR systems that do not predict punctuated and cased outputs, relying on post-processing to restore transcription formatting (Chen, 1999). Per contra, many speech recognition applications, such as financial meeting transcriptions or legal documents, require orthographic text.

In circumstances where orthographic text is required, it is typically achieved through a series of dataset-specific post-processing steps applied to the ASR output, each of which treats a single orthographic feature (Beeferman et al., 1998; Lita et al., 2003; Kim & Woodland, 2003; Gravano et al., 2009; Yuan & Briscoe, 2016). However, there are significant shortcomings to this pipeline approach. Firstly, certain orthographic decisions can only be made using acoustic information rather than text alone. For instance, an inflection in vocal pitch at the end of an sentence can change its meaning from a statement to a question, thus requiring a question mark instead of a period. Secondly, cascading a series of post-processing steps into the speech recognition pipeline may lead to error propagation that hampers overall system performance (Knill et al., 2018; Lu et al., 2019). Finally, the pipeline system is evaluated for each post-processing component individually. This can result in individual components being optimised in isolation, at the expense of lower overall performance due to distribution shift (Sculley et al., 2015). As a result, post-processing can lead to systems failing to accurately predict orthographic transcriptions on datasets where it is required.

These issues and the need for dataset specific pre- or post-processing can be bypassed entirely by designing end-to-end models - from speech directly to orthographic transcripts (Graves & Jaitly, 2014; Chan et al., 2016). E2E models have been shown to outperform traditional cascaded ASR systems, particularly when large amounts of labelled speech data is available (Hannun et al., 2014; Synnaeve et al., 2020; Radford et al., 2022). What is more, E2E ASR systems require a single stage of evaluation; the ASR system is assessed on the cased and punctuated transcription outputs that are generated for the downstream application, giving a single, unified measure of overall performance. However, for the further development and refinement of these systems, it is important to have a benchmark targeting the specific challenges that end-to-end models face.

4 ESB DATASETS

ESB comprises eight English speech recognition datasets, capturing a broad range of domains, acoustic conditions, speaker styles, and transcription requirements. We retain all punctuation, casing and formatting in the transcription outputs. Only annotation mistakes, such as double empty
Table 1: Datasets description and statistics. Speaking style falls into one of three categories: narrated (N), oratory (O) and spontaneous (S). Datasets with multiple speaking styles are shown separated by a comma. Dataset sizes for the train/validation/test splits are quoted in hours of audio data. The transcription format is either normalised (Norm.), punctuated (P) or punctuated and cased (P+C).

| Dataset          | Domain                           | Style | Train/Val/Test | Trans. |
|------------------|----------------------------------|-------|----------------|--------|
| LibriSpeech      | Audiobook                        | N     | 960 / 11 / 11  | Norm.  |
| Common Voice     | Wikipedia                         | N     | 1409 / 27 / 27 | P+C    |
| VoxPopuli        | EU Parliament                     | O     | 523 / 5 / 5    | P      |
| TED-LIUM         | TED talks                         | O     | 454 / 2 / 3    | Norm.  |
| GigaSpeech       | Audiobook, podcast, YouTube      | N, S  | 2500 /12 / 40  | P      |
| SPGISpeech       | Meetings                          | O, S  | 4900 /100 /100 | P+C    |
| Earnings-22      | Meetings                          | O, S  | 105 /5 / 5     | P+C    |
| AMI              | Meetings                          | S     | 78 /9 / 9      | P+C    |
| SwitchBoard      | Telephone                         | S     | 3572 /30 /7    | Norm.  |
| CHiME-4 (optional)| Broadcast news                    | N     | 19/11/7        | P+C    |

spaces, or annotation elements that cannot be considered transcriptions, such as <$unk$>, are corrected. A comprehensive list of all transcription error corrections are detailed in Appendix A.2. As the objective of ESB is to motivate the development of end-to-end ASR, systems must use the same architecture across all datasets without any dataset-specific pre-processing or post-processing. Good performance requires systems capable of handling a range of audio and text conditions without any prior dataset-specific knowledge of the data distributions. The main datasets in ESB are accessible with permissive licensing. We also include three optional paid datasets that challenge interesting and unique domains of speech recognition, but do not require their inclusion for submission to the benchmark. We describe the datasets below and in Table I with additional details in Appendix A.

LibriSpeech [Panayotov et al., 2015] is a standard large-scale dataset for evaluating ASR systems. It consists of approximately 1000 hours of narrated audiobooks collected from the LibriVox project. Whilst instrumental in facilitating researchers to leverage a large body of pre-existing transcribed speech data, its standalone use presents limitations. The audiobook domain provides high-quality recording conditions that result in little to no background noise and the narrated speaking style lacks the acoustic and prosodic features of spontaneous speech. The transcriptions are non-orthographic without punctuation and casing. Since the books read are in the public domain, many contain antiquated language and writing styles atypical of modern-day speech. We anticipate competitive systems to perform extremely well on LibriSpeech [Zhang et al., 2020]. We include LibriSpeech in ESB to facilitate a comparison of performance between ideal speech recognition conditions and the more challenging settings presented by other datasets in the benchmark. We use the standard split of train, validation (dev-clean, dev-other) and test sets (test-clean, test-other).

Common Voice [Ardila et al., 2020] is a series of crowd-sourced open-licensed speech datasets where speakers record text from Wikipedia in various languages. Since anyone can contribute recordings, there is significant variation in both audio quality and speakers. The audio conditions are challenging, with recording artefacts, accented speech, hesitations, and the presence of foreign words. The transcriptions are orthographic, with both casing and punctuation. However, the speaking style remains narrated (a shortcoming shared with LibriSpeech). We use the English subset of version 9.0 (27-4-2022), with approximately 1,400 hours and data splits provided therein.

VoxPopuli [Wang et al., 2021] is a large-scale multilingual speech corpus consisting of data sourced from 2009–2020 European Parliament event recordings. Consequently, it occupies the unique domain of oratory, political speech, largely sourced from non-native speakers. We use the English subset with approximately 550 hours and the canonical data splits.

TED-LIUM [Hernandez et al., 2018] is based on English-language TED Talk conference videos. The transcribed talks cover a range of different cultural, political, and academic topics, resulting in a

https://librivox.org/
technical vocabulary. We use Release 3 edition of the training set with approximately 450 hours and the legacy distribution of validation and test data, consistent with earlier releases for comparison.

**GigaSpeech** (Chen et al., 2021) is a multi-domain English speech recognition corpus curated from audiobooks, podcasts and YouTube. It covers both narrated and spontaneous speech over a variety of topics, such as arts, science and sports. It is the only corpus in the benchmark to cover multiple domains. We use the large subset (2,500 hours) to train and the standard validation and test splits.

**SPGISpeech** (O’Neill et al., 2021) is an English speech recognition corpus composed of company earnings calls that have been manually transcribed by S&P Global, Inc. The transcriptions are fully-formatted according to a professional style guide for oratory and spontaneous speech. We train on the large subset (5,000 hours) and evaluate on the canonical validation and test splits.

**Earnings-22** (De Rio et al., 2022) is a 119-hour corpus of English-language earnings calls collected from global companies. The dataset was developed with the goal of aggregating a broad range of speakers and accents covering a range of real-world financial topics. There is large diversity in the speakers and accents, with speakers taken from seven different language regions. To create train-validation-test splits, we partition the Earnings-22 corpus 90:5:5.

**AMI** (Carletta, 2007; Renals et al., 2007) comprises 100 hours of meeting recordings captured using different recording streams. The corpus contains manually annotated orthographic transcriptions of the meetings aligned at the word level. Individual samples of the AMI dataset contain very large audio files (between 10 and 60 minutes), which we segment to lengths feasible for training most ASR systems (for details, see Appendix A). We use the individual headset microphones (AMI-IHM) version of the dataset and the train, validation and test sets provided therein.

**SwitchBoard (optional)** is a collection of two-sided conversational telephone speech amongst speakers from the US. Recorded over 10 years ago and at a lower sampling rate than the other corpora, it presents a noisy and challenging ASR problem. We partition 5% of the SwitchBoard (Godfrey et al., 1992) corpus to form the validation split. We combine the remainder of the SwitchBoard corpus with Fisher (Cieri et al., 2004a,b) to form a train set consisting of approximately 3,600 hours. The test sets are the Hub5Eval2000 (Linguistic Data Consortium, 2002) data with two subsets: SwitchBoard and CallHome.

**CHiME-4 (optional)** (Vincent et al., 2017) consists of narrated samples from the Wall Street Journal corpus (Garofolo et al., 1993b). Recordings are taken in challenging noisy environments using a 6-channel tablet based microphone array. We limit the official training data to single-channel and 18 hours by randomly selecting one of the six channels for each of the official training recordings. We use the official 1-channel development and test sets in their original annotated form.

SwitchBoard is a popular dataset for assessing ASR systems due to its unique telephone conversation domain. Alongside CHiME-4, these two datasets present challenging and noisy audio conditions. However, both datasets require payment for use. Thus, we include these corpora as optional extras in ESB; the score for these datasets is standalone and does not contribute to the overall benchmark score.

## 5 Evaluation

**System Requirements** ESB requires a single system to be defined and evaluated across the constituent datasets. The system must use the same architecture as well as training and evaluation algorithms for all datasets. This requirement includes using the same data pre- and post-processing of the audio inputs, target transcriptions, and system predictions. There is no restriction on the system being a single model, provided it is defined uniformly across all datasets. Given the range in size of the different datasets, hyper-parameter tuning is permitted, provided the algorithm for hyper-parameters tuning is consistent across datasets. The validation sets from each dataset are used to optimise system configurations and for hyper-parameter tuning, while the test sets are used only for the final evaluation.

Systems submitted to ESB may use any public or private data to train and develop their systems, including unlabelled audio data for pretraining, unlabelled text corpora for training language models (LMs) and labelled audio data for supervised training. However, systems may only use the ESB-distributed versions of the datasets included in the benchmark; in some cases, these datasets include
different data preparation and train/validation/test splits than other public versions. In addition, systems may not use the unlabelled test data for training or development in any way, and may not share information across test samples in any way.

**Metrics** We evaluate system predictions against the target transcriptions using the word error rate (WER) metric. However, to encourage multi-domain systems capable of predicting orthographic transcriptions, we retain all dataset-specific transcription requirements (punctuation and casing) in our evaluation and evaluate systems on a per-dataset level. This decision leads to an orthographic WER that is both punctuation [Kim & Woodland, 2001, 2003] and case [O’Neill et al., 2021] sensitive. Punctuation symbols constitute their own words, such that incorrect punctuation is considered a word substitution error, missing punctuation a word deletion error and additional punctuation a word insertion error. To account for casing, we keep the upper and lower-case character sets distinct. Consequently, incorrect (resp. missing) capitalisation yields a word substitution (resp. deletion) error.

**Benchmark Scoring** We average WERs over individual datasets to give the final score. Through a macro-average, we aim to give a sense of aggregate system performance over all datasets. As with GLUE (Wang et al., 2019b) and SuperGLUE (Wang et al., 2019a), we lack a fair criterion with which to weight the contribution of each dataset, and thus weigh each dataset equally. As LibriSpeech has multiple test sets (test-clean and test-other), we use an unweighted average of the WERs as the score for the dataset when computing the macro-average, so as not to weight it more heavily.

**Leaderboard** The ESB leaderboard keeps track of system submissions (similar to SemEval (Emerson et al., 2022), Kaggle (https://www.kaggle.com), GLUE (Wang et al., 2019b) and SuperGLUE (Wang et al., 2019a)). Data for the benchmark is available for download through Hugging Face Datasets (Lhoest et al., 2021). Each dataset contains standardised audio-transcriptions pairs for the training and validation sets. Only the unlabelled audio samples are included for the test set. To submit a system, one must evaluate the system on the unlabelled audio test data for each of the ESB datasets and upload the predictions to https://huggingface.co/spaces/esb/leaderboard for scoring. The benchmark site details the orthographic WERs for the individual datasets and a macro-average of these scores to determine a system’s position on the leaderboard.

6 **BASELINES**

We evaluate five different systems. These baselines collectively represent current state-of-the-art approaches in E2E ASR. We describe them below, with additional details included in Appendix [B].

**wav2vec 2.0 CTC** wav2vec 2.0 (Baevski et al., 2020) initialised from the official wav2vec 2.0 LARGE LV-60k checkpoint. The checkpoint is pretrained on an unsupervised task with 60k hours of unlabelled audio data from the LibriVox corpus. We follow Baevski et al. (2020) and add a randomly initialised linear layer on top of the Transformer block to predict characters. The system is fine-tuned using the connectionist temporal classification (CTC) (Graves et al., 2006) objective.

**wav2vec 2.0 CTC + n-gram** wav2vec 2.0 CTC with a 5-gram KenLM (Heafield, 2011) to perform LM boosted beam search decoding for CTC. The 5-gram LM is trained on the train split transcriptions for each dataset.

**wav2vec 2.0 AED** An attention-based encoder-decoder (AED) with a wav2vec 2.0 encoder and Transformer (Vaswani et al., 2017) decoder. Encoder weights are initialised with the wav2vec 2.0 LARGE checkpoint and decoder weights with the official BART LARGE (Lewis et al., 2020) checkpoint pretrained on 160 GB of text data. We follow Li et al. (2020) and Babu et al. (2021) in adding a randomly initialised adapter network to interface the encoder and decoder, consisting of three 1-dimensional CNN blocks. The system is fine-tuned using the cross-entropy objective.

**Whisper AED** An AED network initialised with the encoder and decoder weights from the Whisper (Radford et al., 2022) medium.en checkpoint pretrained on a supervised task with 680k hours of weakly labelled audio-transcription data. The system is fine-tuned using the cross-entropy objective.

**Conformer RNN-T** The Conformer Transducer architecture (Gulati et al., 2020), combining a Conformer encoder with an RNN-Transducer (RNN-T) (Graves, 2012) decoder. System weights from

https://www.kaggle.com
Table 2: Baseline performance on the test sets and overall benchmark scores. We report orthographic WERs in %. SwitchBoard, CallHome and CHiME-4 do not contribute to the benchmark score.

| Dataset         | wav2vec 2.0 CTC | wav2vec 2.0 CTC + n-gram | Whisper AED | Conformer RNN-T |
|-----------------|-----------------|--------------------------|-------------|-----------------|
| LibriSpeech     |                 |                          |             |                 |
| test-clean      | 2.9             | 2.4                      | 2.8         | 2.2             |
| test-other      | 7.5             | 5.9                      | 5.8         | 5.2             |
| Common Voice    | 26.1            | 22.2                     | 16.3        | 15.8            |
| VoxPopuli       | 11.4            | 10.2                     | 10.1        | 7.4             |
| TED-LIUM        | 8.4             | 6.7                      | 6.9         | 4.7             |
| GigaSpeech      | 25.3            | 22.0                     | 23.4        | 17.3            |
| SPGISpeech      | 8.1             | 7.1                      | 5.4         | 5.5             |
| Earnings-22     | 26.0            | 31.7                     | 23.6        | 16.0            |
| AMI             | 32.0            | 33.1                     | 19.3        | 14.5            |
| SwitchBoard     |                 |                          |             |                 |
| CallHome        | 16.1            | 12.8                     | 15.3        | 10.0            |
| CHiME-4         | 26.6            | 20.9                     | 24.3        | 15.9            |
| ESB Score       | 17.8            | 17.1                     | 13.7        | 10.6            |

We present performance on ESB for all baselines in Table 2. We quote orthographic WER for each dataset and a macro-average to yield to the overall benchmark score.

Amongst the wav2vec 2.0 baselines trained with unsupervised pretraining, CTC achieves competitive results on LibriSpeech test-clean. Incorporating a LM with CTC + n-gram reduces the benchmark WER score by 0.7% absolute, attaining significant gains on seven of the test sets. On Earnings-22 and AMI, CTC + n-gram performs worse than CTC. The AED architecture significantly outperforms CTC and CTC + n-gram on the datasets with transcription punctuation and character casing, namely Common Voice, SPGISpeech, Earnings-22 and AMI. It performs comparably to CTC + n-gram for the others. Overall, it achieves a score 3.4% lower on ESB.

Whisper AED and Conformer RNN-T incorporate supervised pretraining. Whisper AED improves on wav2vec 2.0 AED for all datasets bar SPGISpeech, achieving the best performance on four of the nine ESB test sets and competitive scores on the others. Conformer RNN-T also performs strongly across the board, achieving the best performance on the remaining four ESB test sets. Whisper and RNN-T achieve comparable ESB scores, with average WERs of 10.6 and 11.0% respectively.

A similar ranking pattern emerges on the optional datasets. CTC + n-gram improves on CTC for all three test sets. wav2vec 2.0 AED performs similarly to CTC and CTC + n-gram on SwitchBoard and CallHome, both test sets that are single-cased and un-punctuated. It fails on CHiME-4, the smallest of the ten training sets, where 18 hours of labelled audio data is unlikely enough to train this system. Whisper AED and Conformer RNN-T yield the strongest results overall, with Whisper the only model to achieve a WER significantly lower than 20% on CallHome.

Notably, we find that results on LibriSpeech do not correlate with ESB score. The most performant results for the LibriSpeech test sets are the two lowest across all datasets, with 2.0 and 4.0% respectively. The most competitive WERs for VoxPopuli, TED-LIUM and SPGISpeech all range between 4.7 and 10.0%. Common Voice, GigaSpeech, AMI, SwitchBoard, CallHome and CHiME-4 all pose challenges even for the best performing systems, with WERs greater than 10.0%. These results indicate that solving ESB is beyond the capabilities of current models and methods.

The NVIDIA NeMo [Kuchaiev et al., 2019] XLARGE checkpoint trained on a supervised task with 24k hours of audio-transcription pairs. The system is fine-tuned using the RNN-T objective.

7 BENCHMARK RESULTS

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https://catalog.ngc.nvidia.com/orgs/nvidia/teams/nemo/models/stt_en_conformer_transducer_xlarge
Table 3 displays the ranked WERs alongside the speaking style for the 12 test sets. Of the audio artefacts, the speaking style matters greatly and is reflected in the benchmark. Five of the seven test sets with the highest WERs contain some degree of spontaneous speech. The next three test sets all contain components of oratory speech. The two test sets with the lowest WERs contain narrated speech alone. Although Common Voice is narrated, it is an outlier and sits in fourth position. This is likely due to its crowd-sourced nature; the high variability in speakers, accents and quality pose difficulties for ASR systems. CHiME-4 is also narrated and ranks in sixth position. This is attributed to the fact it is only 18 hours, has high degrees of noise on the audio inputs and orthographic transcriptions. Whilst SPGISpeech contains oratory and spontaneous speech, it is similar in WER to the test sets that are oratory only (TED-LIUM and VoxPopuli). SPGISpeech potentially contains a much higher proportion of oratory speech than spontaneous and is the largest dataset in ESB (5,000 hours).

Table 3: Minimum WERs for the baselines ranked highest to lowest with speaking style.

| Dataset        | Best Style |  
|----------------|------------|
| GigaSpeech     | 17.3       | N, S    |
| Earnings-22    | 16.0       | S       |
| CallHome       | 15.9       | S       |
| Common Voice   | 14.8       | N       |
| AMI            | 14.5       | S       |
| CHiME-4        | 12.7       | N       |
| SwitchBoard    | 10.0       | S       |
| VoxPopuli      | 7.3        | O       |
| SPGISpeech     | 5.4        | O, S    |
| TED-LIUM       | 4.7        | O       |
| LibriSpeech(o) | 4.0        | N       |
| LibriSpeech(c) | 2.0        | N       |

Figure 1 plots ESB performance against pretraining data. wav2vec 2.0 is pretrained on an unsupervised task with 60k hours of unlabelled data from narrated audiobooks. The three wav2vec 2.0 based systems have the highest ESB score of the five baselines. Whisper AED and Conformer RNN-T are pretrained on 680k and 24k hours of labelled audio data from diverse sources, including multiple domains and speaking styles. These systems achieve competitive performance across the ESB test sets. This suggests that pretraining on diverse, labelled audio data facilitates ASR systems that can be applied to different datasets and domains.

To understand the impact of orthographic transcription features on system performance, we recompute the per-dataset WERs by modifying outputs and targets: (i) remove punctuation, (ii) remove casing, (iii) apply full normalisation. We employ the full English text normaliser from Radford et al. (2022), which removes filler words (“uh”, “uhm”, “mhm”), standardises number formatting (“0” to “zero”) and makes spellings consistent.

Table 4 shows the orthographic ESB scores and the macro-average WERs (per-dataset scores are in Appendix D). Removing punctuation yields a reduction of 2.0% or more for all systems. Punctuation proves difficult for all five systems, but particularly so for CTC + n-gram which exhibits the largest reduction (4.1%). The deep fusion systems have the lowest absolute reductions in WER following punctuation removal (2.3, 2.0 and 2.3% respectively). Casing further reduces the score by 0.5-0.6% for all systems. We observe another 0.5% drop with full normalisation. In total, transcription features account for upwards of 3% of the ESB score for all systems. This reveals the difficulty that orthographic transcription features pose for ASR systems.

To compare the E2E baselines with SoTA systems for individual datasets, we assess the baselines on comparable transcription conditions. Namely, we remove all transcription punctuation and character casing. For GigaSpeech and AMI, we also remove filler words. For Common Voice, we apply the full English text normaliser from Radford et al. (2022). We list the SoTA results as of 09-2022, except for Earnings-22 where the entire dataset is used as a test-set only. Table 5 details the WERs under comparable conditions for the five E2E baselines and individual SoTA. The WER for the best forming E2E systems are to within 2.6% of SoTA for the ESB test sets. The gap is wider for the optional datasets, standing at 7.6% for CallHome. We achieve SoTA results on Common Voice, TED-LIUM and SPGISpeech with Conformer RNN-T, Whisper AED and wav2vec 2.0 AED.
Table 4: The effect of punctuation, casing and full normalisation on benchmark score. We show the orthographic ESB score (no post-processing), score with punctuation removed, score with casing removed and score with full normalisation.

| Score                  | CTC | wav2vec 2.0 | Whisper | Conformer |
|------------------------|-----|-------------|---------|-----------|
|                        |     | CTC + n-gram| AED     | AED       | RNN-T     |
| Orthographic (ESB)     | 17.8| 17.1        | 13.7    | 10.6      | 11.0      |
| - punctuation          | 14.8| 13.0        | 11.4    | 8.6       | 8.7       |
| - casing               | 14.3| 12.4        | 10.8    | 8.0       | 8.1       |
| - normalisation        | 13.7| 11.6        | 10.3    | 7.4       | 7.2       |

Table 5: WER on the ESB test sets under non-orthographic conditions (case and punctuation normalised, removal of fillers for GigaSpeech and AMI, full normalisation for Common Voice). SoTA results are shown alongside those for the five baseline systems. The SoTA results for LibriSpeech are from Zhang et al. (2020), Common Voice Radford et al. (2021), VoxPopuli Conneau et al. (2022), TED-LIUM Zhang et al. (2022), GigaSpeech Chen et al. (2021), AMI Zhang et al. (2022), SwitchBoard and CallHome Tuske et al. (2021), and CHiME-4 Du et al. (2016).

| Dataset            | CTC | wav2vec 2.0 | Whisper | Conformer | Best E2E | SoTA |
|--------------------|-----|-------------|---------|-----------|----------|------|
|                    |     | CTC + n-gram| AED     | AED       | E2E      |      |
| LibriSpeech test-clean | 2.9 | 2.4        | 2.8    | 2.2       | 2.0      | 1.4  |
| LibriSpeech test-other   | 7.5 | 5.9        | 5.8    | 5.2       | 4.0      | 2.6  |
| Common Voice         | 21.9| 16.8       | 12.6   | 12.2      | 9.7      | 10.1 |
| VoxPopuli           | 10.3| 8.3        | 9.8    | 7.2       | 7.1      | 7.0  |
| TED-LIUM            | 8.4 | 6.7        | 6.9    | 4.7       | 5.0      | 5.0  |
| GigaSpeech          | 17.6| 14.3       | 14.3   | 10.5      | 11.7     | 10.5 |
| SPGISpeech          | 4.4 | 3.3        | 2.2    | 2.4       | 2.7      | 2.3  |
| Earnings-22         | 20.4| 20.5       | 19.6   | 11.5      | 12.6     | -    |
| AMI                 | 22.8| 20.6       | 15.2   | 10.4      | 10.5     | 7.8  |
| SwitchBoard         | 14.1| 10.6       | 12.0   | 8.1       | 8.8      | 4.3  |
| CallHome            | 25.9| 20.2       | 19.8   | 14.4      | 22.4     | 6.8  |
| CHiME-4             | 30.7| 25.7       | 62.8   | 11.9      | 13.4     | 10.9 |

respectively. These results demonstrate that E2E systems can be applied effectively to a range of different ASR datasets and domains, although there is still remaining future work on some datasets.

9 Conclusion

We introduce ESB, a benchmark for evaluating end-to-end ASR systems across a broad range of speech domains. The eight datasets in our benchmark include speech recognition domains with different distributions for the audio artefacts and transcription requirements. We motivate the need for dataset-agnostic systems that can be applied across different domains without additional processing. We evaluate five different E2E systems on ESB, demonstrating how a single E2E system can be applied to different datasets and domains. In aggregate, systems pretrained on labelled data achieve better performance than those trained on unlabelled data, but still leave scope for improvement.

We believe that ESB offers a benchmark for developing improved speech recognition systems. Current results show that E2E systems near the performance of state-of-the-art systems on standard measures. Our analysis demonstrates the difficulty that different audio domains as well as punctuation and casing pose for ASR systems. As methods for pretraining ASR systems improve, we expect these issues to narrow as well.
REPRODUCIBILITY STATEMENT

ESB has been designed from the ground up to be accessible to everybody. All mandatory datasets have permissive licences, are free to use, and can be downloaded with a single line of code via the Hugging Face Datasets library\footnote{ESB Datasets: \url{https://huggingface.co/datasets/esb/esb-datasets}}. SwitchBoard and CHiME-4 are optional, as we believe open-sourcing every core aspect of ESB is beneficial for promoting the research and development of ASR systems. In this regard, much work has gone into improving how the community can access the datasets included in ESB. Datasets exceeding 5,000 hours of training data were not considered for the benchmark, thus ensuring ESB remains practically feasible for academic research and that members of the speech community with modest computational requirements can submit to the benchmark. Furthermore, we strongly encourage submissions to include all code, training logs, fine-tuned checkpoints, and evaluation runs necessary to reproduce a results. All of our baseline checkpoints, training logs and code are fully open-sourced and can easily be accessed on the Hugging Face Hub\footnote{ESB Hub: \url{https://huggingface.co/esb}}. Additionally, we describe all details regarding our baselines and evaluation strategies in Appendix B.

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In this section, we give an exhaustive list of the relevant qualitative and quantitative information regarding the datasets used in ESB. Furthermore, we list the minimal transcription error corrections that were performed on the raw transcriptions, in order to ensure systems were trained on suitably formatted text. Finally, we present a diagnostic dataset to help people submitting to ESB find weaknesses in their systems.

A.1 IN-DETAIL DATASETS INFORMATION

In the following section, we give a detailed overview of all relevant statistics for each dataset in ESB. The data is summarised in Tables 6 and 7. For some datasets, we could not reliably retrieve the number of speakers. We denote these missing entries with ?. In addition to the metrics below, we attempted to estimate the signal-to-noise ratio (SNR) of each dataset to quantify their noisiness. We experimented with WADA-SNR \cite{kim2008wada} using an open-source implementation \footnote{SNR: \url{https://gist.github.com/johnmeade/d8d2c67b87cda95cd253f55c21387e75}}, but found our results to be inconclusive with extremely high variance within datasets, and thus deemed them to be largely incorrect. In addition, we tried pre-processing the audio with voice-activity detection (VAD), using the popular webrtcvad \footnote{webrtcvad: \url{https://github.com/wiseman/py-webrtcvad}} tool. However, this also produced unreasonable estimates, again with very high variance within datasets. Combined with a lack of literature on reference numbers, we excluded SNR estimations from our results.

A.2 TRANSCRIPTION ERROR CORRECTION

Below we describe the annotation correction steps taken for each dataset. To re-iterate, we do not consider any of the following pre-processing steps to be any form of normalisation. Instead, we see them as steps to correct erroneously annotated transcriptions or to remove junk annotations, such as \textless unk\textgreater or \textless noise\textgreater. These junk annotations fully unrelated to any kind of punctuation or text and cannot be considered part of speech recognition. All our error corrections steps are reflected in the publicly available code\footnote{ESB Datasets: \url{https://huggingface.co/datasets/esb/esb-datasets}} that is used to download and prepare the benchmark’s datasets.

**LibriSpeech**  No annotation error corrections.

**Common Voice**  Many examples have incorrect trailing quotations marks, e.g "the cat sat on the mat." instead of the cat sat on the mat., probably due to wrong transcription submissions. It does not make sense to wrap a standalone sentence that is considered without any context into quotation marks. In these cases, we strip the trailing quotation marks, leaving: the cat sat on the mat. Additionally double or triple quotation marks are corrected to single quotation marks (e.g. """wait!""" they cried to """"wait!"""" they cried) as double or triple quotation marks do not exist in the English language.

\footnote{LibriSpeech No annotation error corrections.}

\footnote{Common Voice Many examples have incorrect trailing quotations marks, e.g "the cat sat on the mat." instead of the cat sat on the mat., probably due to wrong transcription submissions. It does not make sense to wrap a standalone sentence that is considered without any context into quotation marks. In these cases, we strip the trailing quotation marks, leaving: the cat sat on the mat. Additionally double or triple quotation marks are corrected to single quotation marks (e.g. """"wait!"""" they cried to """"wait!"""" they cried) as double or triple quotation marks do not exist in the English language.}
Table 6: Exhaustive datasets description and statistics (Part 1). Metrics in sample numbers are denoted by (#). Missing speaker number entries are marked with ?. Sampling rate is measured in kilohertz (kHz).

| Domain               | Rec. device       | Source     | Speakers (#) |
|----------------------|-------------------|------------|--------------|
| LibriSpeech (c)      | Audiobook         | Close-talk mic. | Expert        | 1252          |
| LibriSpeech (o)      | Audiobook         | Close-talk mic. | Expert        | 1232          |
| Common Voice         | Wikipedia         | Teleconf.  | Crowd        | 81085         |
| VoxPopuli            | EU Parliament     | Close-talk mic. | Expert        | 1313          |
| TED-LIUM             | TED talks         | Close-talk mic. | Expert        | 2028          |
| GigaSpeech           | Audiobook, pod., YouT. | Close-talk mic. | Expert, Crowd | ?             |
| SPGISpeech           | Financial Meet.   | Teleconf.  | Expert        | 50000         |
| Earnings-22          | Financial Meet.   | Teleconf.  | Expert        | ?             |
| AMI                  | Meetings          | Close-talk mic. | Expert        | ?             |
| Switchboard          | Telephone conv.   | Teleconf.  | Expert        | 543           |
| CHiME-4              | Broadcast news    | Distant Mic. | Expert        | 87            |

| Style                | Non-native | Alignment | License            |
|----------------------|------------|-----------|---------------------|
| LibriSpeech (c)      | Narrated   | No        | Automatic           | CC-BY-4.0     |
| LibriSpeech (o)      | Narrated   | No        | Automatic           | CC-BY-4.0     |
| Common Voice         | Narrated   | Yes       | Manual              | CC0-1.0       |
| VoxPopuli            | Oratory    | Yes       | Automatic           | CC0           |
| TED-LIUM             | Oratory    | Yes       | Automatic           | CC-BY-NC-ND 3.0 |
| GigaSpeech           | Narrated, spontaneous | Yes | Automatic | apache-2.0 |
| SPGISpeech           | Oratory, spontaneous | Yes | Manual | User Agreement |
| Earnings-22          | Oratory, spontaneous | Yes | Automatic | CC-BY-SA-4.0 |
| AMI                  | Spontaneous | Yes       | Automatic           | CC-BY-4.0     |
| Switchboard          | Spontaneous | No        | Manual              | LDC           |
| CHiME-4              | Narrated   | No        | Automatic           | LDC           |

| Samp. Rate (kHz)     | Cased | Punctuated | Orthographic |
|----------------------|-------|------------|--------------|
| LibriSpeech (c)      | 16    | No         | No           |
| LibriSpeech (o)      | 16    | No         | No           |
| Common Voice         | 48    | Yes        | No           |
| VoxPopuli            | 16    | No         | No           |
| TED-LIUM             | 16    | No         | No           |
| GigaSpeech           | 16    | No         | No           |
| SPGISpeech           | 16    | Yes        | Yes          |
| Earnings-22          | 16    | Yes        | Yes          |
| AMI                  | 16    | Yes        | Yes          |
| Switchboard          | 8     | No         | No           |
| CHiME-4              | 16    | Yes        | Yes          |
Table 7: Exhaustive datasets description and statistics (Part 2). Metrics in sample numbers are denoted by (#). Metrics in hours are denoted by (h). Metrics in seconds are denoted by (s). Metrics in word length are denoted by (word).

| Dataset         | Validation (h) | Validation (h) | Test (h) | Test (h) | Mean Length (s) |
|-----------------|----------------|----------------|----------|----------|-----------------|
| LibriSpeech (c) | 460            | 5              | 5        |          | 12.4            |
| LibriSpeech (o) | 500            | 5              | 5        |          | 11.8            |
| Common Voice    | 1409           | 27             | 27       |          | 5.6             |
| VoxPopuli       | 523            | 5              | 5        |          | 10.3            |
| TED-LIUM        | 454            | 2              | 3        |          | 6.1             |
| GigaSpeech      | 2500           | 12             | 40       |          | 4.0             |
| SPGISpeech      | 4900           | 100            | 100      |          | 9.2             |
| Earnings-22     | 105            | 5              | 5        |          | 7.2             |
| AMI             | 78             | 9              | 9        |          | 2.6             |
| Switchboard     | 3572           | 30             | 7        |          | 3.5             |
| CHiME-4         | 19             | 11             | 7        |          | 6.7             |

| Dataset         | Train (#)      | Validation (#) | Test (#) | Test (#) | Mean Length (words) |
|-----------------|----------------|----------------|----------|----------|----------------------|
| LibriSpeech (c) | 132,553        | 2,703          | 2,620    |          | 34.0                 |
| LibriSpeech (o) | 148,688        | 2,864          | 2,939    |          | 31.9                 |
| Common Voice    | 890,116        | 16,335         | 16,335   |          | 9.9                  |
| VoxPopuli       | 182,482        | 1,753          | 1,842    |          | 26.1                 |
| TED-LIUM        | 268,263        | 591            | 1,469    |          | 18.3                 |
| GigaSpeech      | 2,266,371      | 6,750          | 25,619   |          | 12.9                 |
| SPGISpeech      | 1,926,805      | 39,304         | 39,341   |          | 24.1                 |
| Earnings-22     | 52,006         | 2,650          | 2,735    |          | 17.6                 |
| AMI             | 108,502        | 13,098         | 12,643   |          | 7.3                  |
| Switchboard     | 3,712,270      | 21,296         | 4,466    |          | 9.9                  |
| CHiME-4         | 9137           | 6426           | 4096     |          | 16.3                 |
VoxPopuli  No annotation error corrections.

TED-LIUM  Transcriptions in the train set contain instances of the $\langle$unk$\rangle$ token that are not present in the validation and test sets. We remove these tokens from the train set. Additionally, we correct incorrect leading spaces before apostrophes by collapsing spaced apostrophes into un-spaced apostrophes (e.g. it’s to it’s). We omit transcriptions labelled ignore time segment in scoring from our evaluation by filtering them out.

GigaSpeech  We remove official junk tokens ($\langle$sil$\rangle$, $\langle$music$\rangle$, $\langle$noise$\rangle$, $\langle$other$\rangle$) as they cannot be considered audio transcriptions, but rather elements useful for audio classification. We convert the spelled out punctuation to symbolic form (e.g. $\langle$comma$\rangle$ to ,) since the speaker did not pronounce comma, but instead the orthographic comma is meant.

Earnings-22  The Earnings-22 dataset contains audio recordings of financial meetings upwards of 10 minutes in duration. We generate time-stamps for the audio files using the official wav2vec 2.0 CTC + 4-gram model fine-tuned on LibriSpeech (Baevski et al., 2020). We split samples at the time-stamps for punctuation. If the split samples are longer than 20's, we further split them at the longest silence in the utterance. We then train a wav2vec 2.0 CTC system on audio-transcription pairs. We repeat the process of generating time-stamps to yield more robust audio segments.

To form train-validation-test splits, we partition based on audio files, thus keeping speakers distinct between the splits. Files 4420696.wav, 4448760.wav, 4461799.wav, 4469836.wav, 4473238.wav and 4482110.wav form the validation split. Files 4432298.wav, 4450488.wav, 4470290.wav, 4479741.wav, 4483338.wav and 4485244.wav form the test split. The remainder form the train split.

For transcription error correction, we remove the official junk tokens ($\langle$crosstalk$\rangle$, $\langle$affirmative$\rangle$, $\langle$inaudible$\rangle$, $\langle$laugh$\rangle$).

SPGISpeech  No annotation error corrections.

AMI  Audio samples in the AMI meeting corpus vary from between 10 and 60 minutes in duration. We segment the audio samples according the the Kaldi (Povey et al., 2011) recipe for AMI; we split samples longer than 30 words at the time-stamps for punctuation to yield utterance of suitable length for training speech recognition systems.

We remove the junk token $\langle$unk$\rangle$, but otherwise leave the transcriptions un-changed. We fully retain the orthography of the text.

SwitchBoard (optional)  We partition 5% of the SwitchBoard corpus to form the validation split:sw02001-sw02096 and sw04300-sw04387 are partitioned as the validation split, the remainder form the train split.

We remove background noises and non-speech sounds denoted by square brackets, for example [silence]. We remove angle braced words that mark speech to someone, such as $\langle$a.aside$\rangle$, $\langle$b.aside$\rangle$, $\langle$e.aside$\rangle$. We remove partially pronounced words, again denoted by square brackets, for example comm[unity]- is corrected to comm-. We remove annotations for common alternate pronunciations denoted by underscores, for instance okay_I is corrected to okay. Words that contain laughter are donated in square brackets, e.g.: [laughter-because]. We extract the relevant word only: because. We remove the curly braces that denote coinages, changing {alrighty} to alrighty. Filler words such as uh and uhm are annotated in the train set but not the test set. We thus remove these from the train set.

CHiME-4 (optional)  We convert out all spelled out punctuation tokens to their symbolic form (e.g. COMMA to ,). We do not remove any tokens from the originally annotated transcriptions.

\footnote{https://github.com/kaldi-asr/kaldi/tree/master/egs/ami/s5b}
A.3 Diagnostic Dataset

We also provide a new diagnostic dataset consisting of re-annotated portions of ESB using a consistent transcription style, including both normalised and orthographic text formats. As such, it facilitates the reliable evaluation across existing academic datasets and encourages the development of new end-to-end ASR systems.

B Additional Baseline Details

In this section, we present the five end-to-end baseline systems in more detail. We include details on network topology (architecture, number of layers, dimensions), model initialisation, training and evaluation.

**wav2vec 2.0 CTC** A wav2vec 2.0 (Baevski et al., 2020) encoder consisting of seven layers of convolutions (512 channels with strides (5, 2, 2, 2, 2, 2, 2) and kernel widths (10, 3, 3, 3, 3, 2, 2)) followed by a Transformer (Vaswani et al., 2017) network with 24 layers, model dimension 1,024, inner dimension 4,096 and 16 attention heads. To predict characters, we follow Baevski et al. (2020) in appending a randomly initialised linear layer to the output of the Transformer block with dimensionality equal to the size of the vocabulary. The wav2vec 2.0 model is implemented as a Flax (Heek et al., 2020) neural network module in the Hugging Face Transformers (Wolf et al., 2020) library.

We initialise the encoder weights with the official wav2vec 2.0 LARGE checkpoint trained on LibriVox (LV-60k) (Baevski et al., 2020). We define the output vocabulary by computing the frequency of characters in the train set and discarding those below a relative frequency of 0.01%.

For training, we filter audio samples longer than 20 s. We resample all audio data to 16 kHz and normalise utterances to zero mean and unit variance. The system is fine-tuned using the Lingvo (Shen et al., 2019) JAX implementation of the CTC objective. During fine-tuning, we follow the settings of Baevski et al. (2020) and freeze the parameters of the convolutional waveform encoder. We use an Optax (Babuschkin et al., 2020) implementation of the Adam (Kingma & Ba, 2015) optimiser. We train on a single TPU v3-8 (Jouppi et al., 2020) with a batch size of 8 sequences per device, giving an effective batch size of 64 sequences. We train for a total of 50k optimisation steps. We use the slanted triangular learning rate (STLR) (Howard & Ruder, 2018) schedule, linearly increasing the learning rate from zero to a maximum of 1e-4 over the first 5k steps and then linearly decaying it to zero. During training, we evaluate the system on the validation set at 10k step intervals. We select the checkpoint with the best validation performance for evaluation on the test set.

**wav2vec 2.0 CTC + n-gram** We combine the wav2vec 2.0 CTC system with a 5-gram language model. We use the training transcriptions as an LM corpus for each dataset. We compute a MLE of the 5-gram KenLM parameters with Kneser-Ney smoothing (Ney et al., 1994; Heafield et al., 2013). For decoding, we use an LM weight of 0.5 and a word-insertion penalty of 1.5. We use 100 beams and a one pass beam-search decoder from pyctcdecode 11 to perform LM boosted beam search decoding for CTC.

**wav2vec 2.0 AED** We employ an attention-based encoder-decoder (AED) system. The encoder uses the same wav2vec 2.0 network as described in the wav2vec 2.0 CTC baseline. The decoder is also a Transformer network, consisting of 12 layers, model dimension 1,024, inner dimension 4,096 and 16 attention heads. We follow Li et al. (2020) and Babu et al. (2021) in adding a randomly initialised adapter network to interface the encoder and decoder, consisting of three 1-dimensional CNN blocks, each of kernel size 3 and stride 2. The wav2vec 2.0 AED model is implemented as a Flax neural network module in the Hugging Face Transformers library.

We initialise the encoder weights with the official wav2vec 2.0 LARGE LV-60k checkpoint and the decoder model weights with the official BART LARGE (Lewis et al., 2020) checkpoint. The vocabulary is un-changed from the vocabulary of the pretrained BART large model, and thus inherits the BART byte-level Byte-Pair-Encoding (BPE) (Sennrich et al., 2016) tokenizer.

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11 https://github.com/kensho-technologies/pyctcdecode
The wav2vec 2.0 AED system is fine-tuned in much the same way as the CTC system, with the exception of the objective function and learning-rate schedule. The system is fine-tuned using the cross-entropy objective implementation in Optax. We again use the STLR schedule, linearly increasing the learning rate from zero to a maximum of $3e^{-4}$ over the first 500 steps and then linearly decaying it to zero. We select the checkpoint with the best validation set performance for optimising the generation hyper-parameters. We use a beam size of 12 and a maximum sequence length of 225 tokens. We select the length penalty as the value that yields the best performance on the validation set. We use this setting for the final evaluation on the test set.

**Whisper AED**

We employ a second AED network. We use 80-dimensional filterbank features from a 25 ms sliding window and a stride of 10 ms as the inputs to the encoder. The input is passed through two convolutional layers with filter widths of 3 and strides of 1 and 2. The encoder consists of a Transformer network with 12 layers, model dimension 1,024, inner dimension 4,096 and 16 attention heads. The decoder is also a Transformer network with the same dimensions and number of layers. The model is implemented as a PyTorch ([Paszke et al., 2019](https://arxiv.org/abs/1912.01703)) neural network in the official Whisper ([Radford et al., 2022](https://openai.com/research/whisper)) repository.

We initialise the system weights entirely with the official Whisper medium.en checkpoint pretrained on 680k hours of weakly labelled audio data. The tokenizer is the same BPE tokenizer used in GPT-2 ([Radford et al., 2019](https://arxiv.org/abs/1810.04805)).

For training, we truncate audio samples to 30 seconds and resample them to 16 kHz. The system is fine-tuned using the cross-entropy objective. During fine-tuning, we freeze the encoder network. We use the PyTorch implementation of the Adam optimiser. We train on a single NVIDIA A-100 GPU ([Choquette et al., 2021](https://arxiv.org/abs/2106.03885)) with a batch-size of 64. We train for a total of 5k steps. We use the STLR schedule, linearly increasing the learning rate from zero to a maximum of 1e-4 over the first 500 steps and then linearly decaying it to zero. During training, we evaluate the system on the validation set at 500 step intervals. We decode using greedy search with a maximum sequence length of 225 tokens. We select the checkpoint with the best validation performance for evaluation on the test set.

Due to the short period of time between the official Whisper checkpoint release and the submission deadline, we did not exhaustively explore training configurations or generation hyper-parameters (such as beam search). Doing so would most likely have led to improved results. We leave this as future work.

**Conformer RNN-T**

We use 80-dimensional filterbank features from a 25 ms sliding window and a stride of 10 ms as the inputs to the encoder. The encoder consists of a Conformer network with 24 layers, model dimension 1,024, inner dimension 4096, convolutional kernel size 5 and 8 attention heads. The prediction network consists of 2 RNN layers with hidden dimension 640. The transcription network consists of a single feedforward layer with hidden dimension 640. The unit of prediction for the system is SentencePiece ([Kudo & Richardson, 2018](https://arxiv.org/abs/1802.05669)) tokenized text with a vocabulary of size 1,024. The model is implemented as a PyTorch neural network module in the NVIDIA NeMo ([Kuchaiev et al., 2019](https://arxiv.org/abs/1902.11738)) library.

Since the official weights for the Conformer Transducer are not open-sourced, we use the nearest like-for-like open-source replacement. We initialise the model weights from the NVIDIA NeMo XLARGE checkpoint trained on combination of 11 speech recognition datasets totalling nearly 24k hours: LibriSpeech ([Panayotov et al., 2015](https://www.librispeech.org/)), Fisher ([Cieri et al., 2004a,b](https://www.ldc.upenn.edu/LDC2004a/)), SwitchBoard ([Garofolo et al., 1993b](https://www.ldc.upenn.edu/LDC2000a/)), National Speech Corpus (Part 1, Part 6) ([Koh et al., 2019](https://arxiv.org/abs/1905.08473)), VCTK ([Yamagishi et al., 2019](https://arxiv.org/abs/1806.01058)), VoxPopuli ([Wang et al., 2021](https://arxiv.org/abs/2104.05488)), Europarl-ASR (EN) ([Garcés Díaz-Munío et al., 2021](https://arxiv.org/abs/2102.08074)), Multilingual Librispeech (MLS EN, 2k hours subset) ([Pratap et al., 2020](https://arxiv.org/abs/2002.06446)), Mozilla Common Voice (version 8.0) ([Ardila et al., 2020](https://doi.org/10.5281/zenodo.4625632)), and People’s Speech (12k hours subset) ([Galvez et al., 2021](https://arxiv.org/abs/2104.02503)). We train a BPE SentencePiece tokenizer on the transcriptions from the train split for each dataset.

For training, we filter audio samples longer than 20 s. We resample all audio data to 16 kHz and normalise utterances to zero mean and unit variance. We use SpecAugment ([Park et al., 2019](https://arxiv.org/abs/1904.08779)) for data augmentation during training with mask parameter $F = 27$ and ten time masks with maximum

https://catalog.ngc.nvidia.com/orgs/nvidia/teams/nemo/models/stt_en_conformer_transducer_xlarge

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Table 8: Baseline performance on the validation sets and overall benchmark scores. We report orthographic WERs in %. SwitchBoard and CHiME-4 are optional datasets for ESB.

| Dataset          | wav2vec 2.0 CTC | wav2vec 2.0 CTC + n-gram | Whisper AED | Conformer RNN-T |
|------------------|-----------------|--------------------------|-------------|-----------------|
| LibriSpeech test-clean | 2.9             | 2.4                      | 2.8         | 2.2             | 2.0             |
| LibriSpeech test-other    | 7.5             | 5.9                      | 5.8         | 5.2             | 4.0             |
| Common Voice       | 22.8            | 18.9                     | 14.0        | 13.6            | 13.2            |
| VoxPopuli          | 11.4            | 9.1                      | 10.2        | 7.2             | 7.5             |
| TED-LIUM           | 8.7             | 7.1                      | 12.4        | 5.0             | 5.6             |
| GigaSpeech         | 25.9            | 22.5                     | 22.2        | 18.0            | 19.0            |
| SPGISpeech         | 8.1             | 7.1                      | 5.4         | 5.6             | 6.3             |
| Earnings-22        | 26.7            | 38.9                     | 22.8        | 16.0            | 18.3            |
| AMI                | 32.1            | 32.9                     | 20.5        | 16.5            | 17.8            |
| SwitchBoard        | 15.0            | 11.4                     | 11.3        | 8.2             | 8.3             |
| CHiME-4            | 19.6            | 18.9                     | 52.3        | 9.1             | 12.2            |

time mask ration of $p = 0.05$. We set the maximum size of the time mask to $p$ times the length of the utterance and do not use time warping. We fine-tune the system using the NeMo implementation of the Transducer objective. We use the PyTorch implementation of the Adam optimiser. We train on a single NVIDIA A-100 GPU with a batch size of 8 sequences. We train for a total of 100k optimisation steps. We use the STLR schedule, linearly increasing the learning rate from zero to a maximum of 1e-4 over the first 500 steps and then linearly decaying it to zero. During training, we evaluate the system on the validation set at 2.5k step intervals. We decode using greedy search. We find that this yields comparable results to beam-search with a beam-size of 5, but with substantially faster computation times. We select the checkpoint with the best validation performance for evaluation on the test set.

C DEVELOPMENT SET RESULTS

To provide a reference for system development and future work on ESB, we present the best validation set results achieved by our baselines in Table 8.

D ADDITIONAL ANALYSIS RESULTS

Table 9 details the orthographic WER scores for the ESB test sets on a per-dataset level for no post-processing, and under three post-processing conditions: (i) remove punctuation, (ii) remove casing, (iii) apply full normalisation. Table 10 shows the same metrics for the optional test sets.
Table 9: The effect of punctuation, casing and full normalisation on orthographic WER scores for the ESB test sets. We show the WER without post-processing, WER with punctuation removed, WER with casing removed and WER with full normalisation.

| Dataset       | CTC | wav2vec 2.0 | Whisper | Conformer |
|---------------|-----|-------------|---------|-----------|
|               |     | CTC + n-gram| AED     | AED       | RNN-T     |
| LibriSpeech test-clean | 2.9 | 2.4 | 2.8 | 2.2 | 2.0 |
| - punctuation | 2.9 | 2.4 | 2.8 | 2.2 | 2.0 |
| - casing     | 2.9 | 2.4 | 2.8 | 2.2 | 2.0 |
| - normalisation | 2.8 | 2.3 | 2.6 | 2.1 | 1.9 |
| LibriSpeech test-other | 7.5 | 5.9 | 5.8 | 5.2 | 4.0 |
| - punctuation | 7.5 | 5.9 | 5.8 | 5.2 | 4.0 |
| - casing     | 7.5 | 5.9 | 5.8 | 5.2 | 4.0 |
| - normalisation | 7.4 | 5.8 | 5.6 | 5.1 | 3.8 |
| Common Voice | 26.1 | 22.2 | 16.3 | 15.8 | 14.8 |
| - punctuation | 23.9 | 18.8 | 14.4 | 14.2 | 12.3 |
| - casing     | 22.4 | 17.3 | 13.1 | 12.8 | 10.9 |
| - normalisation | 21.9 | 16.8 | 12.6 | 12.2 | 9.7 |
| VoxPopuli    | 11.4 | 10.2 | 10.1 | 7.4 | 7.3 |
| - punctuation | 10.3 | 8.3 | 9.8 | 7.2 | 7.1 |
| - casing     | 10.3 | 8.3 | 9.8 | 7.2 | 7.1 |
| - normalisation | 10.0 | 8.1 | 9.6 | 7.0 | 6.7 |
| TED-LIUM     | 8.4 | 6.7 | 6.9 | 4.7 | 5.0 |
| - punctuation | 8.4 | 6.7 | 6.9 | 4.7 | 5.0 |
| - casing     | 8.4 | 6.7 | 6.9 | 4.7 | 5.0 |
| - normalisation | 7.9 | 6.2 | 6.3 | 4.0 | 4.5 |
| GigaSpeech   | 25.3 | 22.0 | 23.4 | 17.3 | 18.6 |
| - punctuation | 18.2 | 14.9 | 15.3 | 11.0 | 12.4 |
| - casing     | 18.2 | 14.9 | 15.3 | 11.0 | 12.4 |
| - normalisation | 17.5 | 13.9 | 14.3 | 10.2 | 11.3 |
| SPGISpeech   | 8.1 | 7.1 | 5.4 | 5.5 | 6.3 |
| - punctuation | 5.8 | 4.6 | 3.3 | 3.6 | 3.9 |
| - casing     | 4.4 | 3.3 | 2.2 | 2.4 | 2.7 |
| - normalisation | 4.2 | 3.0 | 2.0 | 2.2 | 2.4 |
| Earnings-22  | 26.0 | 31.7 | 23.6 | 16.0 | 17.6 |
| - punctuation | 20.9 | 21.0 | 20.1 | 12.1 | 13.3 |
| - casing     | 20.4 | 20.5 | 19.6 | 11.5 | 12.6 |
| - normalisation | 19.3 | 18.8 | 18.3 | 9.9 | 10.2 |
| AMI          | 32.0 | 33.1 | 19.3 | 14.5 | 15.1 |
| - punctuation | 26.0 | 25.1 | 16.8 | 12.2 | 12.3 |
| - casing     | 24.8 | 23.7 | 15.5 | 10.8 | 11.0 |
| - normalisation | 23.7 | 22.0 | 15.0 | 10.3 | 10.2 |
Table 10: The effect of punctuation, casing and full normalisation on orthographic WER scores for the optional test sets. We show the WER without post-processing, WER with punctuation removed, WER with casing removed and WER with full normalisation.

| Dataset     | CTC | wav2vec 2.0 | CTC + n-gram | Whisper AED | Conformer RNN-T |
|-------------|-----|-------------|---------------|-------------|-----------------|
|             | CTC | AED         |               |             |                 |
| SwitchBoard | 16.1| 12.8        | 15.3          | 10.0        | 10.8            |
| - punctuation | 14.1| 10.6        | 12.0          | 8.1         | 8.8             |
| - casing    | 14.1| 10.6        | 12.0          | 8.1         | 8.8             |
| - normalisation | 14.0| 10.4        | 10.2          | 7.8         | 8.3             |
| CallHome    | 26.6| 20.9        | 24.3          | 15.9        | 23.3            |
| - punctuation | 25.9| 20.2        | 19.8          | 14.4        | 22.4            |
| - casing    | 25.9| 20.2        | 19.8          | 14.4        | 22.4            |
| - normalisation | 25.7| 19.9        | 17.1          | 13.5        | 22.1            |
| CHiME-4     | 29.2| 26.8        | 56.9          | 12.7        | 14.2            |
| - punctuation | 28.3| 24.4        | 59.2          | 11.7        | 13.3            |
| - casing    | 27.4| 23.4        | 59.0          | 11.0        | 12.6            |
| - normalisation | 30.7| 25.7        | 62.8          | 11.9        | 13.4            |