MORE SPEAKING OR MORE SPEAKERS?

Dan Berrebbi^{‡*}, Ronan Collobert[†], Navdeep Jaitly[†], Tatiana Likhomanenko[†]

[‡]Carnegie Mellon University, [†]Apple

ABSTRACT

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Self-training (ST) and self-supervised learning (SSL) methods have demonstrated strong improvements in automatic speech recognition (ASR). In spite of these advances, to the best of our knowledge, there is no analysis of how the composition of the labelled and unlabelled datasets used in these methods affects the results. In this work we aim to analyse the effect of number of speakers in the training data on a recent SSL algorithm (wav2vec 2.0), and a recent ST algorithm (slimIPL). We perform a systematic analysis on both labeled and unlabeled data by varying the number of speakers while keeping the number of hours fixed and vice versa. Our findings suggest that SSL requires a large amount of unlabeled data to produce high accuracy results, while ST requires a sufficient number of speakers in the labelled data, especially in the low-regime setting. In this manner these two approaches improve supervised learning in different regimes of data composition.

Index Terms- self-supervised, self-training, speakers

1. INTRODUCTION AND RELATED WORKS

Self-supervised learning (SSL) [1, 2, 3, 4], self-training (ST), or pseudo-labeling (PL), [5, 6, 7, 8, 9, 10] and their combination [11, 12] have produced strong improvements in the accuracy of ASR systems when a large amount of unlabeled data is available. These works showed results on small amount of supervised data, and also studied how they scale with more unlabeled data. A recent work [13] has analysed the accuracy of open-sourced SSL and supervised models under different conditions (e.g. conversational speech) and across population subgroups (e.g. gender, accent) after training on a fixed dataset. In this work, we aim to understand the dependence between the number of speakers in the labeled/unlabeled training data and the accuracy of SSL/ST trained models¹.

Recent work [14] showed that forcing speaker-disentangled representations during SSL pre-training improves accuracy on a set of content-related downstream tasks. Authors of [15] established that fewer than 50 speakers and around 10 to 20 hours of speech per language were sufficient for the development of a usable ASR system for low resource languages.

Table 1: Proposal summary on data collection for ST and SSL. We denote S_L and S_U as the number of speakers and H_L and H_U as the total number of hours in the labeled and unlabeled data respectively. With '*' we mark cases where the thresholds are crucial for acceptable performance. We do not test configurations with less than 10h (100h) of labeled (unlabeled) data.

Training	$\# S_L$	$\# S_U$	$\# H_U$
wav2vec (97M) $H_L \ge 10h$	> 120 > 120 > 120	> 2000	$ > 500h^*$
wav2vec (317M), $H_L \ge 10h$		> 1000	$> 500h^*$
slimIPL (255M), $H_L = 10h$	$ > 120^*$	> 1000	$\begin{vmatrix} > 100h \\ > 100h \end{vmatrix}$
slimIPL (255M), $H_L > 10h$	> 120	> 1000	

Later wav2vec 2.0 [1] showed that ASR can be built with even 10min of supervision as long as a large unlabeled dataset is available. Compared to [15] which used HMM-based models we use Connectionist Temporal Classification (CTC) [16] loss with a transformer model and the latest developments in ASR training pipelines (e.g. SpecAugment [17]).

Earlier work [18] investigated the effect of varying the amount of labeled and unlabeled data for SSL and ST in computer vision and reported that the accuracy of SSL and ST techniques tends to converge to the same value as the number of labels grows, but found surprisingly different levels of sensitivity to varying data amount across these techniques.

To inform more optimal data collection, we study how SSL and ST algorithms perform as the number of speakers is varied, while keeping the number of hours fixed and vice versa for both the labeled and the unlabeled datasets. A prior work [19] provides insights for dependence on speaker diversity in SSL trained only with synthesized data and in limited configurations. To the best of our fknowledge, we are the first to perform a systematic survey focused on the role of the number of speakers for SSL and ST methods. Our findings encourage re-thinking of the data collection process for ASR, especially in a low-resource supervision and lead us to propose an appropriate composition which is summarized in Table 1. We highlight the main results from Table 1 as: i) for low-resource settings, it is critical to have a sufficient number of speakers in labeled data; ii) the improvement from increasing the number of speakers in both labeled and unlabeled data

^{*}Work done during internship at Apple.

¹In this study labeled and unlabeled data come from the same domain. However unlabeled data contains not only clean speech as labeled data but also noisy speech.

plateaus after a certain threshold; iii) it is critical for SSL to have enough unlabeled data, while for ST it is critical to have enough speakers in the labeled data.

2. EXPERIMENTAL SETUP

2.1. Generation of Data Subsets

All our experiments were performed using LibriSpeech [20]. Labeled sets: We took *train-clean-100* with 100h and 251 speakers and sampled different number of speakers and hours. Unlabeled sets: We took *train-clean-360* and *train-other-500* with 860h and 2087 speakers in total and sample different number of speakers and hours. Note, there is no overlap in speakers between LibriSpeech provided sets (train, dev or test).

Table 2: Statistics on speakers extracted from *train-clean-100* (100h), *train-clean-360* (360h) and *train-other-500* (500h).

100h		36	ö0h	500h		
#speakers	Female %	#speakers	Female %	#speakers	Female %	
24	54.1	115	48.7	145	48.3	
60	53.3	230	46.5	290	50.7	
120	51.6	460	47.2	580	49.3	
185	52.4	921	47.7	1166	48.4	
251	49.8	-	-	-	-	

We describe below a sampling strategy for labeled subsets; the same sampling strategy is applied to sample from unlabeled subsets. To achieve fair and consistent comparisons, we implemented a sampling process satisfying the following conditions. First, the speakers subsets are randomly sampled from train-clean-100: smaller subsets of speakers are included in any larger subset of speakers. In Table 2 we show statistics on the sampled speakers gender: percentage of female and male speakers is well balanced across our sampled subsets. Second, for every speaker we sample different amount of minutes preserving the inclusion of subsets per speaker: e.g. if we have two subsets containing 2min and 10min for the same speaker, then the 2min audio samples are included in the 10min ones. In LibriSpeech every speaker has at most 25min of audio, thus some combinations cannot be generated, e.g. 25h with 24 speakers. The summary of all subsets is detailed in Table 3.

2.2. Models and Algorithms

For this study we run various models with three different training algorithms – supervised training, continuous pseudo-labeling with slimIPL [7] and SSL with wav2vec 2.0 [1].

2.2.1. Supervised Training and Self-Training

For both supervised training and ST with slimIPL we closely follow slimIPL [7] and use the same architecture and training pipeline. Models are trained with English letters token

Table 3: Statistics of labeled (randomly extracted from *train-clean-100*) and unlabeled (randomly extracted from *train-clean-360* and *train-other-500*) subsets of LibriSpeech with different amount of speakers and hours.

Name	#hours	#speakers	#min per	#utterances	#words	
- tunio	miouro	nopeanero	speaker		Total	Unique
10h-24	10.1	24	25.0	2846	97355	12108
10h-60	9.9	60	10.0	2836	95772	12860
10h-120	9.8	120	5.0	2793	96015	12969
10h-185	9.5	185	3.2	2709	93466	12897
10h-251	9.6	251	2.4	2728	94469	13098
25h-60	25.1	60	25.0	7172	243251	20989
25h-120	24.8	120	12.5	7050	243367	21114
25h-185	24.7	185	8.1	6986	241711	21444
25h-251	24.6	251	6.0	7017	243180	21705
50h-120	50.3	120	25.0	14282	492905	29546
50h-185	49.7	185	16.2	14046	486793	30008
50h-251	49.6	251	12.0	14109	488881	30418
100h-251	100.6	251	24.0	28539	990101	41572
108h-260	110.6	260	25.0	32410	1078816	43286
108h-520	107.4	520	12.5	31438	1051319	44639
108h-1040	105.5	1040	6.2	31007	1026921	45863
108h-2087	103.9	2087	3.1	30951	1017510	46809
216h-520	221.3	520	25.0	64633	2165301	60360
216h-1040	214.8	1040	12.5	62895	2091514	62186
216h-2087	211.5	2087	6.2	62803	2071413	63737
430h-1040	442.5	1040	25.0	129419	4307931	82906
430h-2087	423.4	2087	12.4	125090	4147820	84694
860h-2087	860.5	2087	24.7	252702	8413454	162561

set², CTC loss, identical SpecAugment [17] parameters, and Adagrad optimizer [21]. The acoustic model is the same transformer model introduced in slimIPL, except that we encode positions with a recently proposed CAPE [22] instead of relative positional embedding [23] to speed up training by 2-3x and decrease the memory footprint significantly. All models (255M parameters) are trained on 8 GPUs of A100-40GB for a maximum of 500-600k updates. We use dynamic batches that pack ~ 290 s of audio per GPU. For supervised training we use dropout and layer drop [24] of 0.3 for 50h, 0.4 for 25h and 0.5 for 10h, while for slimIPL we use 0.3 for 108h, 0.25 for 216h, 0.2 for 430h, and 0.1 for 860h of unlabeled data. The slimIPL cache size is set to 1000 (which was the optimal cache size for 10h and was a robust setting for 100h of supervision) with cache probability of 0.1. We additionally search over the proportion of labeled/unlabeled data λ varying it in $\{1, 2, 5, 10\}$ and the burn in period before pseudo-labels are used (after 20k, 30k, 40k steps) for best results.

2.2.2. Self-Supervised Training

For wav2vec 2.0 [1] we use open-sourced recipes from fairseq³ for both Base (95M) and Large (317M) models.

²26 letters augmented with the apostrophe and a word boundary token.

³ https://github.com/facebookresearch/fairseq/blob/main/examples/wav2vec/

First, we pre-train on our unlabeled subsets with different number of hours and speakers: we use the LibriSpeech pre-training recipe and only change the encoder dropout for different amount of pre-training hours: 0.05 (0.2) for 860h, 0.1 (0.3) for 430h, 0.15 (0.4) for 216h, and 0.2 (0.5) for 108h for a Base (Large) model. The remaining parameters are unchanged. Pre-trained models are fine-tuned on different labeled subsets using the 10h recipe for all 10h/25h subsets and the 100h recipe for 50h/100h subsets using the same parameters as in the open-sourced recipe.

2.2.3. Evaluation

We evaluate models on standard LibriSpeech sets, *dev-clean*, *dev-other*, *test-clean*, *test-other*. For the sake of space we report only dev sets in all Figures. For supervised training we run experiments with three different seeds and report mean and standard deviation of the word error rate (WER). For ST and SSL experiments we run only one seed and report its WER on *dev-other* set.

3. RESULTS

3.1. Impact of Dataset Composition on Supervised Training

Figure 1 shows dependence between speakers and number of hours for supervised training. Clearly, more speakers is helpful for the training but at some point the gain diminishes (185 speakers).



Fig. 1: Dependence of supervised training on the amount of data and speakers.

3.2. Impact of Dataset Composition on ST

Figure 2 (row 1, column 3) shows the heatmap of WER for different configurations of number of speakers in labeled and unlabeled data for slimIPL. Increasing the number of speakers is beneficial until certain point in both labeled and unlabeled data. Row 4, column 3 shows that in the low-supervision setting having a large number of speakers in labeled data is critical. For example, with only 10 hours of labeled data, having 24 speakers results in a WER of 28% (with 100h unlabeled data) and 19% (with 860h unlabeled data) but having 120

speakers reduces the WER to 23% and 15.5% respectively. Row 5, column 3, on the other hand shows that the number of speakers in the unlabeled set does not make as much of a difference (it is possible that this becomes more important when the number of speakers is much smaller than the 260 we started with). Row 6, column 3 shows the expected trend that increasing the number of labeled/unlabeled hours produces gains in accuracy⁴.

3.3. Impact of Dataset Composition on SSL

From Figure 2, columns 1, 2, rows 3 and 4 we see that both Base and Large wav2vec 2.0 models show small improvements with more speakers in the labeled data. Columns 1, 2, rows 1 and 2, likewise show small improvements from more speakers in unlabeled data. In contrast, from columns 1, 2, row 6, we see a drastic gain in accuracy from increasing number of unlabeled hours (e.g., the large model achieves a WER of 49% with 10h of labeled data and 100h of unlabeled data, averaged over runs with different number of speakers; this number reduces to 23% with 400h of unlabeled data averaged over runs with different number of speakers).

3.4. Comparing ST and SSL

For SSL, the number of speakers in labeled data is not critical, whereas it is essential for ST, especially in low data regimes. In contrast, the amount of unlabeled data is critical for SSL models and not as critical for ST models. For both types of algorithms, the low-supervision regime is different from highsupervision regime and the influence of number of speakers quickly diminishes in both labeled and unlabeled data once a sufficient number of speakers is assembled.

4. DISCUSSION & CONCLUSION

Our observations in self-training and self-supervised learning in ASR suggest that data collection may be revisited in low supervision to improve results in ASR. For self-training it is better to have more speakers in labeled data, when the labeled data size is fixed. It is also beneficial to have around 1K speakers in the unlabeled data. SSL on the other hand is affected more by the number of hours of unlabeled data than it is by the number of speakers in the unlabeled data. In this manner these two approaches improve supervised learning in different regimes of dataset composition, which can explain the reason of their combination success [11, 12]. Our paper does not address the question of how to select from accents, lexical content and noise conditions for improving the performance of ST and SSL and we leave this for future research.

⁴Note that each point on the grid of the heatmap reflects averages over multiple runs with different, but fixed amount of training data. However, manually inspecting subsets confirmed that the trends look similar for settings with fixed, individual number of training hours.



Fig. 2: Word error rate (WER) heatmaps on LibriSpeech *dev-other* for SSL with wav2vec 2.0 Base (column 1) and Large (column 2), and ST with slimIPL (column 3). We consider WER as a function of 4 variables: unlabeled hours, unlabeled speakers, labeled hours and labeled speakers, and plot heatmap for every pair of variables while we average over the other two variables. The black part corresponds to missing configurations for which we do not have enough data in LibriSpeech. As seen in Table 1 we observe that i) for low-resource settings, it is critical to have a sufficient number of speakers in labeled data; ii) the improvement from increasing the number of speakers in both labeled and unlabeled data plateaus after a certain threshold; iii) it is critical for SSL to have enough unlabeled data, while for ST it is critical to have enough speakers in labeled data.



Fig. 3: Word error rate (WER) heatmaps on LibriSpeech *dev-clean* for SSL with wav2vec 2.0 Base (column 1) and Large (column 2), and ST with slimIPL (column 3). We consider WER as a function of 4 variables: unlabeled hours, unlabeled speakers, labeled hours and labeled speakers, and plot heatmap for every pair of variables while we average over the other two variables. The black part corresponds to missing configurations for which we do not have enough data in LibriSpeech. As seen in Table 1 we observe that i) for low-resource settings, it is critical to have a sufficient number of speakers in labeled data; ii) the improvement from increasing the number of speakers in both labeled and unlabeled data plateaus after a certain threshold; iii) it is critical for SSL to have enough unlabeled data, while for ST it is critical to have enough speakers in labeled data.

Unlabeled data	Labeled data	wav2vec 2.0 Base WER %		wav2vec 2.0 Large WER %		slimIPL WER %	
		dev-clean	dev-other	dev-clean	dev-other	dev-clean	dev-other
	10h-24	28.2	47.4	32.3	52.6	16.8	28.3
	10h-60	27.1	45.4	31.8	50.6	-	-
	10h-120	26.4	44.3	30.8	49.7	12.9	23.2
	10h-185	26.2	44.1	30.4	49.2	-	-
	10h-251	25.9	43.9	30.2	48.9	13.2	23.0
108h-260	25h-60	24.4	42.7	27.4	46.5	-	-
10011 200	25h-120	23.8	41.7	26.3	45.0	8.0	17.7
	25h-185	23.3	41.2	2.06	44.7	-	-
	25h-251	23.4	41.1	25.8	44.4	8.3	17.4
	50h-120	15.2	35.4	18.2	38.1	6.2	14.4
	50h-185	14.9	34.1	18.1	37.6	-	-
	306-231	14.7	33.7	18.0	37.2	0.0	14.0
	10h-24	27.2	46.0	30.7	49.1	15.5	26.4
	10h-60	26.7	44.3	32.2	47.5	- 10 (-
	10h-120	25.9	43.4	29.2	46.6	12.6	21.9
	10n-185 10h 251	25.9 25.9	43.0	29.0	46.2	12.2	-
	1011-231 25h 60	23.8	45.1	26.0	40.0	15.5	22.4
108h-520	25h-120	24.2	41.0 70.6	20.9	44.J 121	80	- 16 A
	25h-120	23.5	40.0	20.1	43.4	0.0	10.4
	25h-251	22.9	40.2	25.9	42.5	82	163
	50h-120	15.1	34.5	17.3	36.0	6.0	13.7
	50h-185	14.5	33.4	16.9	35.3	-	-
	50h-251	14.3	32.6	16.9	34.7	6.0	13.5
	10h-24	31.2	50.3	30.7	49.3	16.1	26.7
	10h-60	30.6	48.6	30.3	47.5	-	-
	10h-120	29.8	47.7	29.6	46.4	12.8	22.2
	10h-185	29.7	47.3	29.6	46.1	-	-
	10h-251	29.3	47.2	29.3	45.9	13.0	21.5
108h-1040	25h-60	27.4	45.2	26.4	43.8	-	-
	25h-120	26.8	44.5	25.9	42.5	7.8	15.7
	25h-185	26.3	44.0	26.3	42.9	-	-
	25h-251	26.1	43.8	25.2	42.1	8.1	15.9
	50h-120	16.4	36.5	18.3	36.0	6.0	13.2
	50h-185	16.0	35.5	17.9	35.7	-	-
	306-231	15.0	35.0	17.9	35.5	0.0	13.0
	10h-24	25.2	41.8	30.9	49.6	15.4	25.6
	10h-60	24.8	40.3	30.4	4/.8	10.0	-
108h-2087	10h-120	24.2	39.8	29.5	46.8	12.8	21.1
	10n-185 10h 251	24.3	39.6 20.5	29.6	40.9	12.0	
	25h 60	24.3	39.3 27 0	29.4	40.3	12.9	21.3
	2511-00 25h-120	22.0	37.0	20.5	43.9 10 7	- ר ד	- 15.6
	25h-185	21.0	36.5	25.5	43.3		15.0
	25h-251	21.0	36.5	25.3	42.2	80	15.6
	50h-120	13.6	30.8	18 7	36.6	6.0	13.0
	50h-185	13.2	29.9	18.3	36.2		-
	50h-251	13.0	29.4	18.3	35.9	6.1	12.8
	10h-24	18.4	33.7	18.6	33.6	14.3	23.5
	10h-60	18.2	32.5	17.7	31.8	-	-
	10h-120	17.7	31.8	17.2	30.9	10.7	18.4
	10h-185	17.7	31.4	17.2	30.5	-	-
	10h-251	17.6	31.4	17.2	30.4	11.5	19.7
216h 520	25h-60	16.6	30.7	15.4	29.2	-	-
216h-520	25h-120	16.0	30.1	14.8	28.1	6.7	14.0
	25h-185	15.9	29.5	14.8	27.8	-	-
	25h-251	15.9	29.4	14.8	27.7	6.8	13.8
	50h-120	10.9	26.6	10.5	24.3	5.8	13.0
	50h-185	10.9	25.5	10.3	23.4	-	-
	50h-251	10.9	25.1	10.3	23.1	6.0	13.1

Table 4: Detailed Word Error Rate (WER) for all models trained on different subsets of labeled and unlabeled data from Table 3.Figures 2 and 3 are shown based on these results.

Unlabeled data	Labeled data	wav2vec 2.0 Base WER %		wav2vec 2.0 Large WER %		slimIPL WER %	
		dev-clean	dev-other	dev-clean	dev-other	dev-clean	dev-other
	10h-24	17.6	31.2	18.6	32.5	14.4	23.1
	10h-60	16.8	29.6	18.0	31.2	-	-
	10h-120	16.5	29.2	17.5	30.3	10.6	18.0
	10h-185	16.6	29.1	17.5	30.2	-	-
	10h-251	16.5	28.9	17.4	29.8	11.2	18.5
216h-1040	25h-60	15.6	28.1	15.7	28.5	-	-
210111040	25h-120	14.9	27.4	15.1	27.5	6.7	13.3
	25h-185	14.7	26.9	15.0	27.1	-	-
	25h-251	14.6	26.8	15.0	27.0	6.7	13.3
	50h-120	10.5	24.8	10.6	23.1	5.8	12.5
	50h-185	10.2	23.8	10.6	22.5	-	-
	50h-251	9.9	23.7	10.3	22.1	5.8	12.4
	10h-24	16.8	29.0	19.7	33.5	13.9	22.7
	10h-60	16.3	28.3	19.3	31.8	-	-
	10h-120	16.0	27.4	19.0	31.2	10.4	16.8
	10h-185	16.4	27.3	18.7	31.0	-	-
	10h-251	16.1	27.3	18./	30.7	10.8	17.8
216h-2087	25h-60	14.6	26.3	16.6	29.0	-	-
	25h-120	14.4	25.6	16.1	28.0	0.0	13.2
	25h-185	14.3	25.5	15.9	27.7	-	-
	250-251 50h 120	14.5	25.0	15.9	27.5	0./ 5.7	12.9
	50h-120	10.5	22.8	11.2	23.3	5.7	12.2
	50h-251	10.2	22.2	11.1	23.0	5.7	12.3
	10h-24	12.7	25.6	13.2	24.4	13.2	20.9
	10h-60	12.0	22.0	12.7	22.9	-	
	10h-120	11.9	23.3	12.1	22.1	9.7	16.0
	10h-185	11.7	23.0	12.1	21.9	-	
	10h-251	11.9	22.8	12.1	21.7	9.9	16.8
	25h-60	10.8	22.5	10.2	20.3	-	
430h-1040	25h-120	107	21.6	9.7	19.5	6.0	11.4
	25h-185	10.3	21.3	9.6	19.1	-	-
	25h-251	10.2	21.3	9.5	18.9	6.2	12.0
	50h-120	8.8	20.4	7.2	16.7	5.0	10.4
	50h-185	8.8	19.8	7.1	16.2	-	-
	50h-251	8.2	19.3	6.9	15.9	4.9	10.1
	10h-24	12.2	23.5	13.4	24.6	13.7	21.0
	10h-60	11.9	22.4	13.1	23.0	-	-
	10h-120	11.8	21.7	12.8	22.5	9.3	15.2
430h-2087	10h-185	11.5	21.4	12.8	22.1	-	-
	10h-251	11.6	21.3	12.8	21.9	9.9	16.0
	25h-60	10.6	20.8	10.6	20.3	-	-
10011 2007	25h-120	10.3	20.0	10.3	19.6	6.1	11.2
	25h-185	10.2	19.6	10.1	19.1	-	-
	25h-251	10.3	19.6	10.1	19.1	6.1	11.2
	50h-120	8.5	18.8	7.4	16.4	5.0	10.1
	50h-185	8.3	18.1	7.3	15.8	-	-
	50h-251	8.0	17.8	/.4	15.7	4.9	10.2
	10h-24	9.2	17.3	8.9	16.3	12.1	18.8
	10h-60	8.8	16.4	8.6	15.1	-	-
	10h-120	8.7	15.9	8.4	14.9	10.0	15.6
	10h-185	8.6	15.5	8.5	14.5	-	-
	10h-251	8.7	15.4	8.4	14.5	10.4	16.3
860h-2087	25n-60	/.9	15.3	0./	13.0	-	-
	23n-120 25h 185	1.1	14./	0.5	12.7	6.2	11.1
	23N-183	/.0	14.5	0.4	12.2		-
	201-201 50h 100	/.0	14.3	0.4	12.1	0.2	11.1
	50h 185	0.3	14.3	4.9	10.7	4.3	9.5
	50h-251	0.5	13.0	4.9	10.5	- 16	- 0.5
	JUII-2JI	0.2	13.4	+.7	10.2	- +.0	2.5

Table 5: (Continue) Detailed Word Error Rate (WER) for all models trained on different subsets of labeled and unlabeled datafrom Table 3. Figures 2 and 3 are shown based on these results.

5. REFERENCES

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