AVOID OVERTHINKING IN SELF-SUPERVISED MODELS FOR SPEECH RECOGNITION

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ABSTRACT

Self-supervised learning (SSL) models reshaped our approach to speech, language and vision. However their huge size and the opaque relations between their layers and tasks result in slow inference and network overthinking, where predictions made from the last layer of large models is worse than those made from intermediate layers. Early exit (EE) strategies can solve both issues by dynamically reducing computations at inference time for certain samples. Although popular for classification tasks in vision and language, EE has seen less use for sequence-to-sequence speech recognition (ASR) tasks where outputs from early layers are often degenerate. This challenge is further compounded when speech SSL models are applied on out-of-distribution (OOD) data. This paper first shows that SSL models do overthinking in ASR. We then motivate further research in EE by computing an optimal bound for performance versus speed trade-offs. To approach this bound we propose two new strategies for ASR: (1) we adapt the recently proposed patience strategy to ASR; and (2) we design a new EE strategy specific to ASR that performs better than all strategies previously introduced.

Index Terms— Self-Supervised Learning, Overthinking

1. INTRODUCTION

Even though SSL models significantly improved state of the art performances on most speech tasks [1–5], major drawbacks weaken their impact. First their huge stack of transformer layers [6] make inference time quite slow, which is non desirable for on-device problems for instance. Second as their training is task agnostic [7], each layer role and performance for ASR task remains unclear [8]. In particular such large models are prone to overthinking [9] which occurs when an accurate prediction is reached at an intermediate layer $i$ and computations of layers $j > i$ are wasteful and potentially destructive in terms of prediction quality.

Orthogonal to static model compression strategies such as knowledge distillation [10, 11] or weight pruning [12], early exit methods [13] address the overthinking problem by dynamically reducing computations for certain samples at inference time. Typical approaches add lightweight exit heads on top of some layers. Those heads, called branches, compute exit scores usually based on confidence metrics such as entropy of softmax prediction distribution. During inference if an intermediate layer’s exit head outputs an exit score bigger than a fixed threshold, the model outputs this layer’s prediction and stops forward computation, saving precious time.

Despite their huge success in vision [14] and language [15–20] and their portfolio of potential applications, EE have not yet met a huge enthusiasm in speech [21–23] and in particular in ASR [24]. Early exiting is very challenging for ASR. First ASR is a complex sequence-to-sequence task in which models fail to get 100% accuracy for most samples. On the contrary most EE approaches were designed for classification problems [13, 15] in which early predictions are very likely to be correct and constant across layers. This enabled [15], inspired by early stopping strategies [25], to introduce a patience criteria which outperformed confidence based EE techniques on BERT [26]. Secondly, speech SSL models are commonly fine-tuned or used out of the box in OOD setups in which audio differs in language, noise level, type of speech and accent from the pre-training (and fine-tuning). This frequent scenario in ASR research remains very challenging [27] and it is legit to wonder whether EE strategies would be effective in such setup.

The contributions of this work are summarized as follows:

• We show that ASR models do overthinking and analyze such phenomenon for in-domain and OOD scenario;
• We compute theoretical lower bounds of speed/quality trade-offs for EE strategies through dynamic programming;
• We adapt patience based EE strategies to suit ASR task;
• We introduce overlang: a vocabulary based new EE strategy designed from our findings on overthinking in ASR.

2. MOTIVATIONS: OVERTHINKING IN ASR

For an audio sample $x$ and a model composed of $N$ layers, we will note $\hat{y}_i(x)$ the output prediction of layer $i \in \{i_{\text{min}}, ..., N\}$. We assume that the model has exit heads on top of each layer except the $i_{\text{min}}$ first layers which predictions are often degenerated. $y_i(x)$ is a character sequence that can be compared to the reference transcription $y(x)$.

Following [9] a model overthinks for an input $x$ if

\[
\exists i < N \text{ such that } \text{error}(\hat{y}_i(x)) \leq \text{error}(\hat{y}_N(x)) \tag{1}
\]

If Equation 1 is an equality then only time is wasted but performance is not impacted (we will call this scenario overthinking without degradation), but it could also be that quality of output is degraded. EE strategies aim to find trade-offs between saving computations, so outputting $\hat{y}_i$ with a small $i$, and having $\hat{y}_i$ quality better than $\hat{y}_N$ (overthinking scenario) or at least not too much degraded.

2.1. Experimental details

Model - We used Hubert Large model [1] pre-trained (PT) on Librilight [28] 60k hours and fine-tuned (FT) on Librispeech [29] 960 hours. We used English characters as token set. We added exit heads over all layers after layer 10. Our exit heads are made of a feed-forward module and a CTC [30] head. Heads training (HT) was done on Librispeech 100h clean split, using the intermediate CTC loss [31]. More details and hyperparameters are released in ESPnet [32].

Data - We used three datasets for inference: dev-clean and dev-other sets from Librispeech [29], and the English dev set from Common-voice 5.1 [33]. Table 1 exhibits the distribution shifts for those sets.

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1 For not overloading formulas we may write $\hat{y}_i$ and $y$.
2 Thus significantly smaller than [24] thus increasing computation savings.
3 We call the sets respectively Libri_dev_clean, Libri_dev_other and CV_en.
as accents, noise level and distributions (audiobooks/human generated sentences) differ. We see that \textit{Libri\_dev\_clean} is fully in-distribution while \textit{Libri\_dev\_other} is partly OOD and \textit{CV\_en} is totally OOD.

**Table 1: Distribution shifts for the inference sets.**

|                  | \textit{Libri\_dev\_clean} | \textit{Libri\_dev\_other} | \textit{CV\_en} |
|------------------|----------------------------|-----------------------------|-----------------|
| \textit{PT & FT} | in distribution            | in distribution             | OOD             |
| \textit{HT}      | in distribution             | OOD                         | OOD             |

2.2. Do speech SSL model overthink?

Large networks such as SSL models are very prone to overthinking as shown in [9, 14, 15]. However, those studies mostly targeted classifications tasks such as sentiment analysis [15]. For such task, it seems intuitive that for some $i$, layers $j \geq i$ will output the same class [15]. On the other hand ASR is a complex sequence to sequence task in which the model’s layers are refining a predicted sentence. In most cases $\hat{y}_i(x)$ is different from $y(x)$ for all $i \in [1,N]$. Thus we can think that overthinking does not occur since refining the prediction until the last layer could be more beneficial than harmful due to the complexity of the task.

In Figure 1 we show that SSL models do overthinking for ASR: bar $i$ is the percentage of samples per set for which the best prediction (for word error rate, WER) is reached first at layer $i$. We remark that:

- For all sets less than 10% of the samples need to go to the last layer to reach best prediction, which is a clear case of overthinking.
- For \textit{Libri\_dev\_clean} a non negligible portion of the samples reach their best prediction very early (i.e. before layer 20) whereas for the two OOD sets (\textit{Libri\_dev\_other} and \textit{CV\_en}) more than 70% of the samples need to wait the last 4 layers to reach best prediction.

Additionally to Figure 1, our aim is to differentiate if the model is overthinking without degradation (so only wasting time) or is wasting time and degrading performances. In other terms, among samples that reach best prediction before the last layer what is the share for which the last layer remains the best one? We found that it is more than 90% for the Librispeech sets (so mainly overthinking without degradation) whereas for \textit{CV\_en} more than 22% of the samples predictions are degraded when reaching the last layer.

2.3. Lower bound for early exit strategies

Using every layer predictions for each sample we computed the best performances for any reachable number of saved computations through dynamic programming. Optimum are convex (see Figure 2) for the 3 datasets showing that (up to some point) computation savings increase relatively faster than quality degradation which is desirable.

![Figure 1: Overthinking in ASR for in-domain and OOD sets.](image1)

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We formally note $\zeta$ the criterion (taking only boolean values) such that for a sample $x$ the model exits at layer $i^* = \min_i \{ i | \zeta(\hat{y}_i(x)) = 1 \}$.

5As this could have the opposite effect, i.e. favor very early exit for short sentences, we will report results for sentences of more than 10 words only.

![Figure 2: Theoretical bounds to early exits trade-offs](image2)
We note $T(x)$ (simplified as $T$) the number of frames of sample $x$ and $C$ the number of tokens. $f_{t,c}(x)$ is the output of the softmax exit branch at layer $i$, for frame $t \in [1, T]$ and token $c \in [1, C]^6$.

### 3.1. Confidence based methods

We first tried the commonly used entropy based confidence score [13], computed from the softmax output following Eq. 2.

$$\text{score}(\hat{y}_i(x)) = - \frac{1}{T \cdot C} \sum_{t=1}^{T} \sum_{c=1}^{C} f_{t,c}(x) \cdot \log(f_{t,c}(x)) \quad (2)$$

Following [24] we also tried a variant where the confidence score is given by the average over frames of the maximum softmax probability instead of the entropy of the distribution. As a well calibrated model would be confident about accurate prediction, our criteria is given by Equation 3.

$$\zeta(\hat{y}_i(x)) = \mathbb{I}_{\text{score}(\hat{y}_i(x)) < \tau} \quad (3)$$

where $\tau$ is a fixed threshold and $\mathbb{I}$ is the indicator function.

### 3.2. Patience based methods

Strategies introduced in Section 3.1 can however be weak when a model is overconfident or poorly calibrated and cannot handle regression cases [15]. Inspired by early stopping, PABEE [15] solved those issues by introducing patience based strategies. The principle is that criteria $\zeta$ allows exit at layer $i$ if the prediction at layer $i$ is consistent with the predictions of the few layers before $i$. It enables to (1) avoid unstable predictions; (2) exit when the model somehow converged to a prediction; and (3) indirectly predict from an ensemble of layers. Formally with a distance $d$, a threshold $\tau$ and a patience threshold $\rho \in \mathbb{N}$, the patience strategy can be written as in Equation 4.

$$\zeta(\hat{y}_i(x)) = 1 \Leftrightarrow \forall j \in [i - \rho, i], \text{dist}(\hat{y}_j(x), \hat{y}_{j-1}(x)) < \tau \quad (4)$$

Distances proposed in [15] (e.g. L2 distance of two predictions) cannot be applied to sequential outputs. We used two distances for patience strategies: cross-entropy at the logits level and Levenshtein distance at the output sentence level.

### 3.3. Overlang : a vocabulary based strategy

Finally, we propose a novel criterion that directly targets the EE aim: output high quality predictions while avoiding overthinking. As we stick to Hubert configuration [1] we adopt characters as our token set. Predicted words (sequences of letters delimited by spaces) may thus be any combination of characters which are potentially out-of-vocabulary (e.g. due to misspelling)$^8$. A first observation is that when an early layer prediction is of poor quality, most of its incorrect words are out-of-vocabulary. Table 2 provides examples of predicted sentences from early layers with several of such out-of-vocabulary errors. These predictions are phonetically proximate to the reference, but consist of many invalid words – we can reasonably detect these by checking against a known vocabulary.

Overthinking happens only when accurate predicted words (which are in-vocabulary) are modified by later layers and so cannot occur on words that are out-of-vocabulary (under assumption that out-of-vocabulary words are incorrect)$^9$. As our model was never guided by any language model in its training, we assume that when early layers predict a word that is in vocabulary this word is very likely to be the accurate prediction. Overthinking may then happen if this correct word is changed to another in or out-of-vocabulary word.

This leads us to the following criteria : exit is allowed at layer $i$ if the prediction of this layer does not contain too many out of vocabulary words. We note $\mathcal{V}$ our English vocabulary$^{10}$. We define $W(\hat{y}_i(x))$ in Equation 5 as the proportion of in-vocabulary words in layer $i$’s prediction, where $\text{card}(\cdot)$ is the cardinal of a set and $\text{length}(\cdot)$ is the number of words of a sentence.

$$\text{W}(\hat{y}_i(x)) = \frac{\text{card}\{w \in \hat{y}_i(x) \text{ such that } w \in \mathcal{V}\}}{\text{length}(\hat{y}_i(x))} \quad (5)$$

For a threshold $\tau$, an exit criterion can be derived as in Equation 6:

$$\zeta(\hat{y}_i(x)) = 1 \text{ if } W(\hat{y}_i(x)) \geq \tau \quad (6)$$

This criterion is orthogonal to the ones defined in Section 3.1 and 3.2 so that they also can be combined together. We combined $\zeta$ defined in Equation 6 with a patience criterion on the $W(\hat{y}_i(x))$ values. For a chosen integer $\rho$, if $W(\hat{y}_j(x))$ is constant for $j \in [i - \rho, i]$ then the model exits at layer $i$ even if $W(\hat{y}_j(x)) < \tau$. For a given $\rho$ and $\tau$, Equation 7 defines overlang, our vocabulary based EE criterion,

$$\zeta(\hat{y}_i) = \max(\mathbb{I}\{W(\hat{y}_i) \geq \tau\}, \mathbb{I}W(\hat{y}_{i-1}) = \ldots = W(\hat{y}_{i-\rho})) \quad (7)$$

Where max is equal to one if at least one of the indicators is satisfied.

### 4. RESULTS AND ANALYSIS

#### 4.1. Additional details on experiments

Table 3 gathers the values we used for thresholds in our EE strategies.

| Strategy | Measure | Range of hyperparameters |
|----------|---------|--------------------------|
| Confidence | Entropy | $\tau \in \{0.002, 0.0025, 0.003, \ldots, 0.006\}$ |
| Confidence | Maximum Probability | $\tau \in \{0.93, 0.935, 0.94, \ldots, 0.97\}$ |
| Patience | Cross-Entropy | $\tau \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$ |
| Patience | Levenshtein distance | $\tau \in \{0.05, 0.07, 0.1, 0.13, 0.2\}$ |
| Overlang | - | $\tau \in \{0.6, 0.625, 0.65, \ldots, 0.95\}$ |

#### 4.2. Efficiency of the strategies

Figure 3 presents the speed/performance trade-offs of the EE strategies introduced in Section 3 for Libri_dev_other set$^{11}$. We add in green the optimal bound curve computed in Section 2.3 and in red the

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$^6$Our models are CTC-based only however the strategies can be applied to encoder-decoder or any other architecture.

$^7$For the maximum probability variant, the inequality sign is changed.

$^8$We note that this findings and method also apply for any type of subword.

$^9$This assumption is acceptable given that proportion of out-of-vocabulary words in reference transcription (e.g. named entities) is quite small.

$^{10}$Given by any English dictionary, we used english-words library.

$^{11}$Similar behaviors are observed on the two other inference sets.

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Table 2: Example ASR errors flagged by an out-of-vocabulary check.

| Reference Sentence | Predicted sentence |
|--------------------|--------------------|
| he ased on seeing the prisiners | now active exploitation was required |
| he asked on seeing the prisoners | he used on seeing the prisoners |
We first remark that the patience based strategies (both with cross-entropy patience) provide an example of how the strategies can behave (see Table 5).

First we see that the language strategy benefits over the confidence one as *overthing* is not in-vocabulary: *overlang* exits two layers later only but with a correct sentence. On the contrary, the patience strategy using cross-entropy exits at the last layer as the output probability distribution is not stable (in terms of entropy), thus overthinking a lot.

4.4. Additional remarks on experiments

We add empirical findings of practical interest for the readers:

- Combining patience and confidence strategies does not improve over confidence ones contrary to combinations of patience and *overlang*. A plausible explanation is that when prediction is constant across layers, *overlang* ratio $W$ of in-vocabulary words is constant and so if $W < \tau$ the model do not exit early. On the other hand, confidence based methods are not impacted by this scenario because even if predicting the same sentence across different layers, the model usually becomes more confident about its prediction and thus quickly reaches the confidence threshold and exits.

- No behavioral difference was found between in-distribution and OOD. It demonstrates the feasibility of EE strategies for OOD.

5. CONCLUSION AND FUTURE DIRECTIONS

We demonstrate that overthinking happens in ASR for both in-domain and OOD scenario. Our introduced *overlang* strategy as well as confidence-based methods enable reaching good speed/quality trade-offs thus avoiding overthinking for some samples. We believe that research in this topic is very promising for a wide range of applications such as on-device systems or semi-supervised ASR where pseudo-labels could be generated (more rapidly) by early layers for some samples as [34] showed that bootstrapping from poor quality pseudo-labels is viable.

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**Table 5**: Early exit layers for utterance 1630-96099-0016.

| Strategy       | Exit Layer | Sentence                  |
|----------------|------------|----------------------------|
| Reference      | -          | he left everything behind  |
| Patience (cross-entropy) | 24         | he left everything behind  |
| Confidence (entropy)  | 13         | he left everthing behind  |
| Overlang        | 15         | he left everything behind  |

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