Latest Advances in End-to-End Speech Recognition

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November 2, 2022

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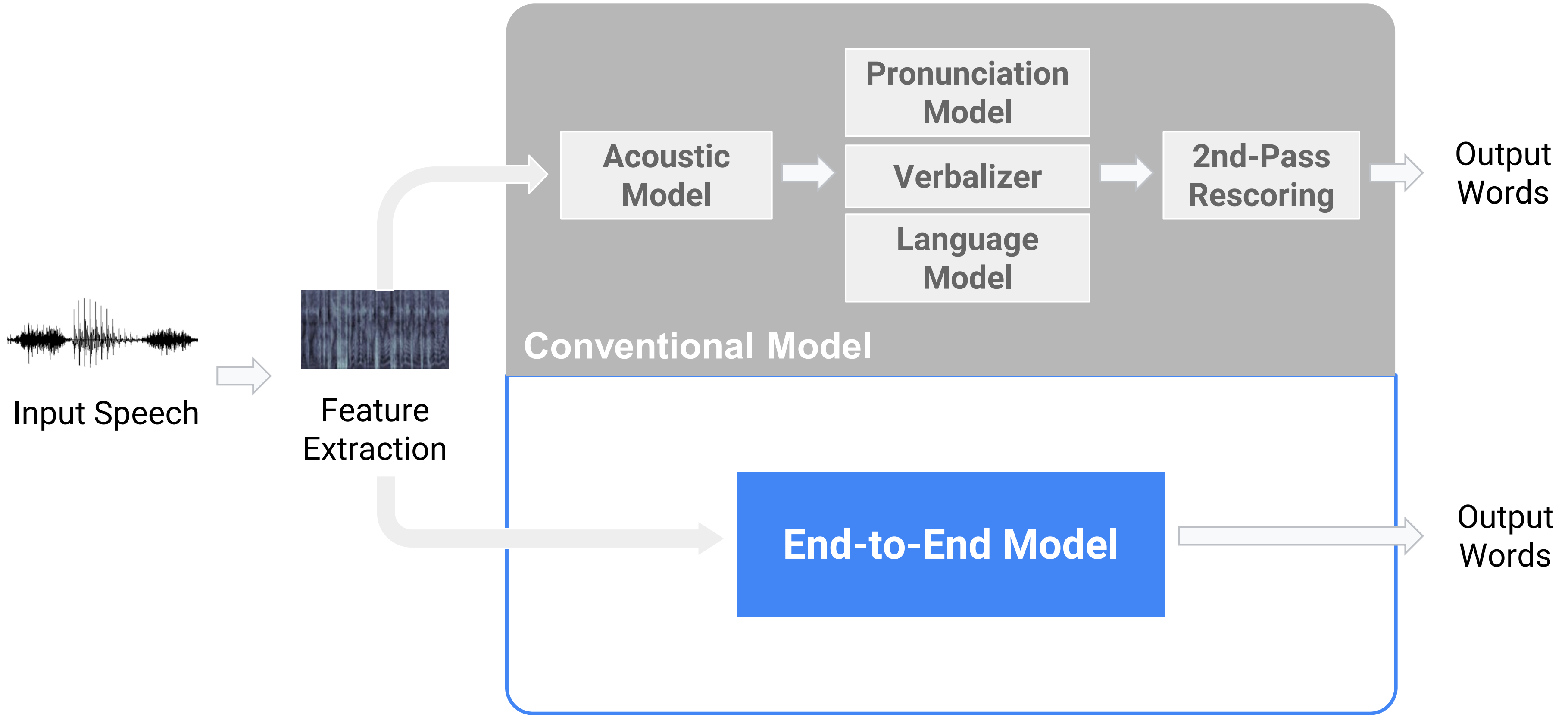
A Joint Effort Between Google Brain, Hardware and Speech Teams

What is End-to-End ASR?

“A system which directly maps a sequence of input acoustic features into a sequence of graphemes or words.”

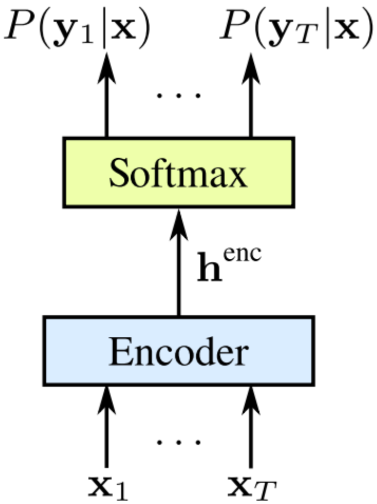
"A system which is trained to optimize criteria that are related to the final evaluation metric - word error rate."


Input Speech
Feature Extraction
Acoustic Model
Pronunciation Model
Verbalizer
Language Model
2nd-Pass Rescoring
Output Words
Conventional Model
End-to-End Model
Output Words

Historical Development of End-to-End ASR

Connectionist Temporal Classification (CTC)

[Graves et al., 2006]




```
B B c B B a a B B t
B c c B a B B B B t
        ...
B c B B a B B t t B
```

$$P(\mathbf{y}|\mathbf{x}) = \sum_{\hat{\mathbf{y}} \in \mathcal{B}(\mathbf{y},\mathbf{x})} \prod_{t=1}^{T} P(\hat{y}_t|\mathbf{x})$$

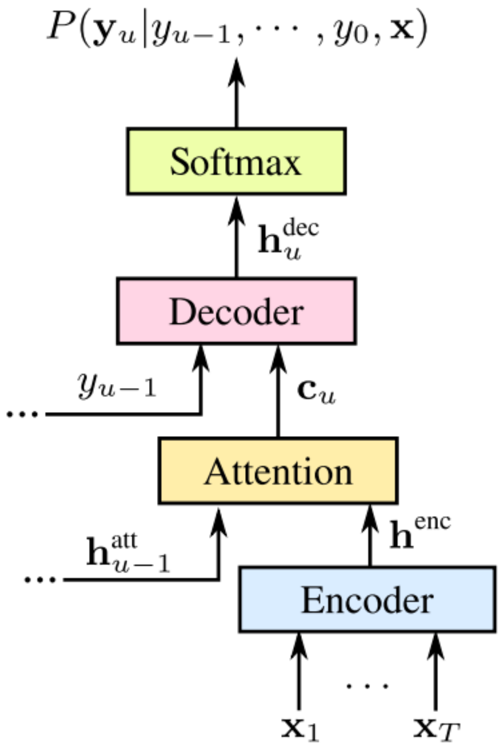
- CTC introduces a special symbol - blank (denoted by B) - and maximizes the total probability of the label sequence by marginalizing over all possible alignments.
- No frame-level alignment is needed.

CTC-Based End-to-End ASR

- [Graves & Jaitly, 2014] proposed a system with character-based CTC which directly output word sequences given input speech
- LM incorporated into first-pass decoding; easy integration with WFSTs
  - [Hannun et al., 2014] [Maas et al., 2015]: Direct first-pass decoding with an LM as opposed to rescoring as in [Graves & Jaitly, 2014]
- Large-scale GPU training; data augmentation; multiple languages
  - [Hannun et al., 2014; DeepSpeech] [Amodei et al., 2015; DeepSpeech2]: Large scale GPU training; Data Augmentation; Mandarin and English
- Using longer span units: words instead of characters
  - [Soltau et al., 2017]: Word-level CTC targets, trained on 125,000 hours of speech. Performance close to or better than a conventional system, even without using an LM!
  - [Audhkhasi et al., 2017]: Direct Acoustics-to-Word Models on Switchboard
- And many others ...

Attention-based Encoder-Decoder Models

[Chan et al., 2015][Chorowski et al., 2015]



- Encoder (analogous to AM):
  - Transforms input speech into higher-level representation
- Attention (alignment model):
  - Identifies encoded frames that are relevant to producing current output
- Decoder (analogous to PM, LM):
  - Operates autoregressively by predicting each output token as a function of the previous predictions

Comparing Various End-to-End Approaches

[Prabhavalkar et al., 2017]

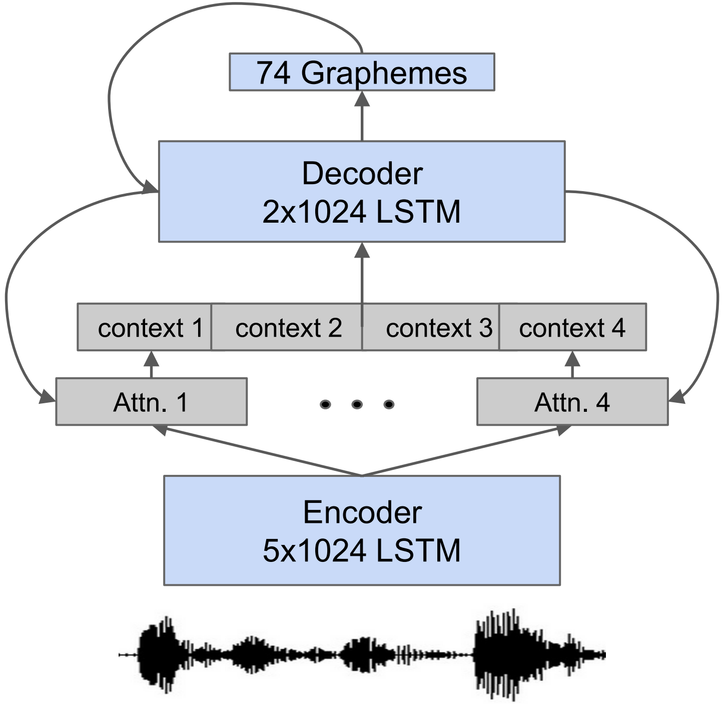
Model	Online/Offline	VoiceSearch Word Error Rate (%)
Conventional Model	online	9.9
	offline	8.6
CTC-Grapheme (no LM)	online	53.4
Attention-based Model	offline	11.7

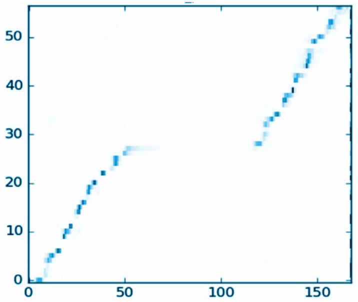
- Decoding CTC-grapheme models without an LM performs poorly.
- Attention-based model performs better, but still lags behind a conventional model.

2018: Further Improvements

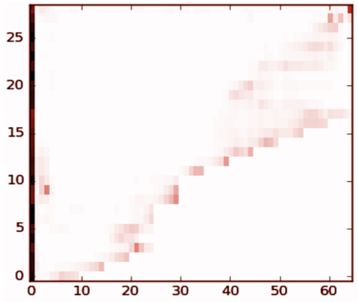
Multi-headed Attention

[A. Vaswani, 2017][Chiu et al., 2018]





Single Headed Attention



Multi-Headed Attention

- Multi-headed attention examines different parts of the utterance for each predicted label.
- Model looks predominantly towards previous frames.

Word Pieces

[Schuster, 2012][Chiu et al., 2018]

- We want to use subword units longer than graphemes:
  - Longer units have a lower LM perplexity
  - Longer units gives improved decoder efficiency
- Word pieces is a good longer-unit choice [Schuster, 2012]
  - Has shown good results for RNN-T [Rao, ASRU 2017]
- Word piece model (WPM) details
  - Trained to maximize LM likelihood on training data
  - Position dependent, determined determinstically
  - Units back off to characters → No OOVs

Good Afternoon → _go o d _aft er noon

Minimum Word Error Rate (MWER)

[Stolcke et al., 1997][Povey, 2003][Prabhavalkar et al., 2018]

- End-to-end models are typically trained by optimizing cross entropy loss (i.e., maximizing log-likelihood of the training data)

$$\mathcal{L}_{\text{CE}} = \sum_{(\mathbf{x},\mathbf{y}^*)} \sum_{u=1}^{L+1} -\log P(y_u^* | y_{u-1}^*, \cdots, y_0^* = \langle \text{sos} \rangle, \mathbf{x})$$

- Training criterion does not match metric of interest: Word Error Rate
- MWER optimizes the expected word error rates:

$$\mathcal{L}_{\text{werr}}(\mathbf{x}, \mathbf{y}^*) = \mathbb{E}[\boxed{\mathcal{W}(\mathbf{y}, \mathbf{y}^*)}] = \sum_{\mathbf{y}} P(\mathbf{y}|\mathbf{x}) \mathcal{W}(\mathbf{y}, \mathbf{y}^*)$$

Number of Word Errors

Optimization improvements
[Chiu et al., 2018]

- Scheduled Sampling [S. Bengio, 2015]
  - Feed back in the prediction from the model rather than the true previous prediction
  - Helps prevent overfitting
- Label smoothing [C. Szegedy, 2016]
  - Take the logit class with maximum probability and smooth it over the remaining labels
  - Helps prevent overfitting
- Sync training [P. Goyal, 2017]
  - Gradient updates between workers are synchronized
  - Leads to faster convergence and better model quality

Comparison to Conventional Model

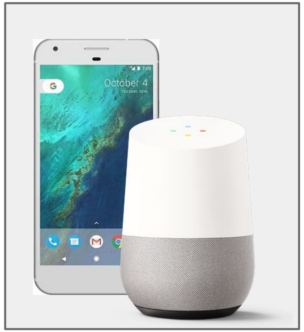
[Chiu et al., 2018]

Model	1st Pass Model Size	VoiceSearch Word Error Rate (%)
Conventional Server	0.1GB (AM) + 2.2 GB (PM) + 4.9 GM (LM) = 7.2 GB	6.7
Attention-based Model	**0.4 GB**	**5.6**

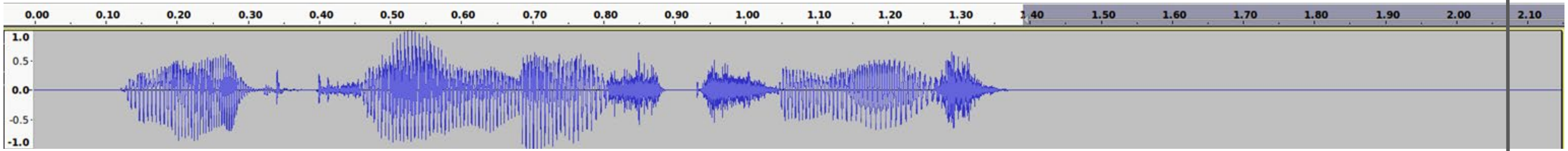
- **16%** relative performance improvement over conventional model
- **18X smaller** than conventional model in 1st pass
- Main drawback: model is **not streaming**

2019-2020: Online End-to-End Models for Pixel 4

Streaming Speech Recognition



Finalize recognition &
Taking action / fetching the search results

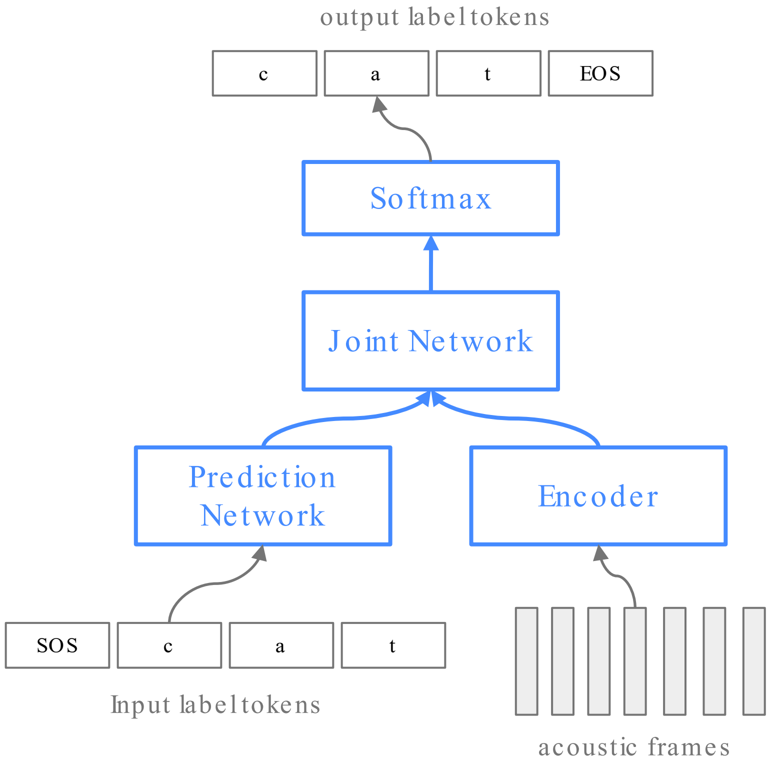


Recognize the audio

Recurrent Neural Network Transducer (RNN-T)

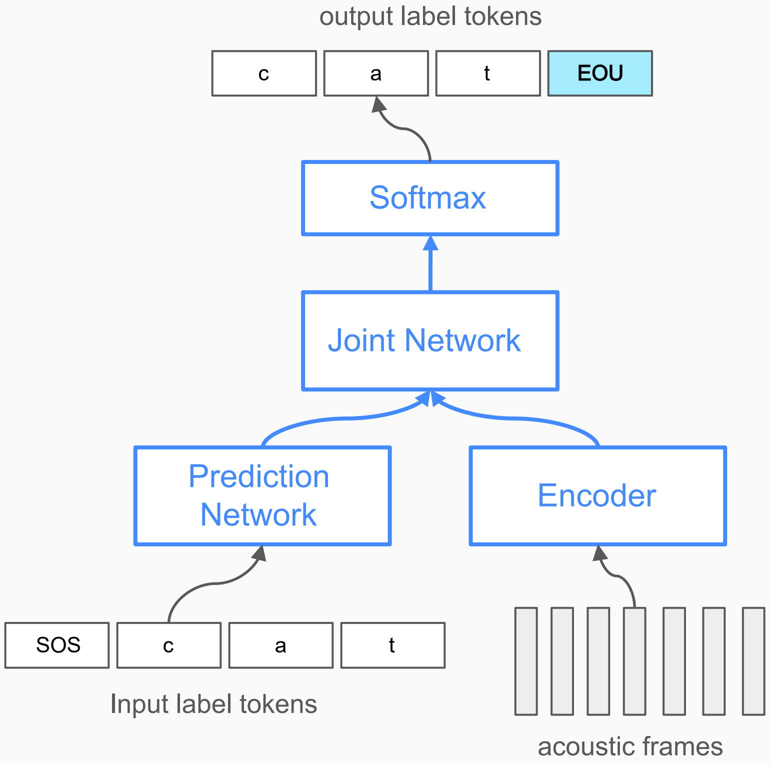
[Graves, 2012], [Rao et al., 2017], [He et al., 2018]

- Encoder Network
  - Set of recurrent layers (like am AM)
- Prediction Network
  - recurrent LM
- Joint Network
  - combines AM and LM predictions
- Jointly optimized end-to-end
- No alignment needed.
- Streaming model.



Low Latency RNN-T (RNN-T Endpointer)

[Li et al., 2020][Sainath et al., 2020]



OLD

EOU Modeling

Jointly models End-Of-Utterance (EOU) with ASR in RNN-T for better latency.

Accurate EOU Timing

Based on **time alignment** of the end of last word.
Adding **early and late penalties** for EOU predictions.

Reducing Premature EOU

EOU terminates beam search paths during inference.
Sequence training with **MWER**.

[1] Shuo-Yiin Chang, et.al, "Joint Endpointing and Decoding with End-to-end Models", ICASSP 2019

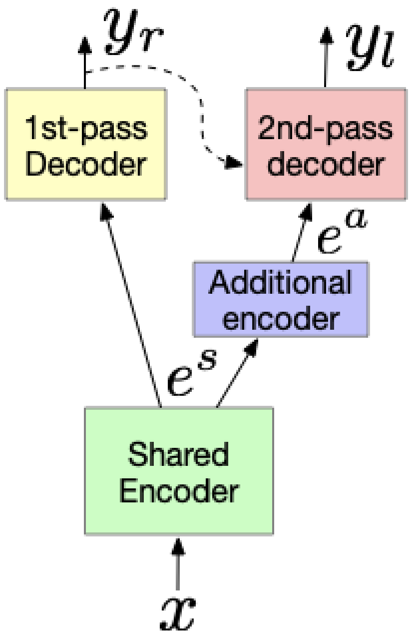
[2] Bo Li, et.al, "Towards Fast and Accurate Streaming End-to-End ASR", submitted to ICASSP 2020

Model	VoiceSearch Word Error Rate (%)	EOU Latency (90 percentile)
On-Device RNN-T + VAD	7.4%	860ms
On-Device RNN-T EP	**6.8%**	**790ms**

RNN-EP gives better WER and latency tradeoff compared to RNN-T + VAD

Second-pass LAS Rescoring

[Sainath et al. 2019][Sainath et al., 2020]



- 1st-pass RNN-T for streaming applications.
- 2nd-pass full-context attention-based LAS decoder for better quality.
- Shared encoder for a compact model.

Model	**VoiceSearch Word Error Rate (%)**
On-Device RNN-T EP	6.8%
+ LAS Rescoring	**6.1%**

Comparison to Conventional Model

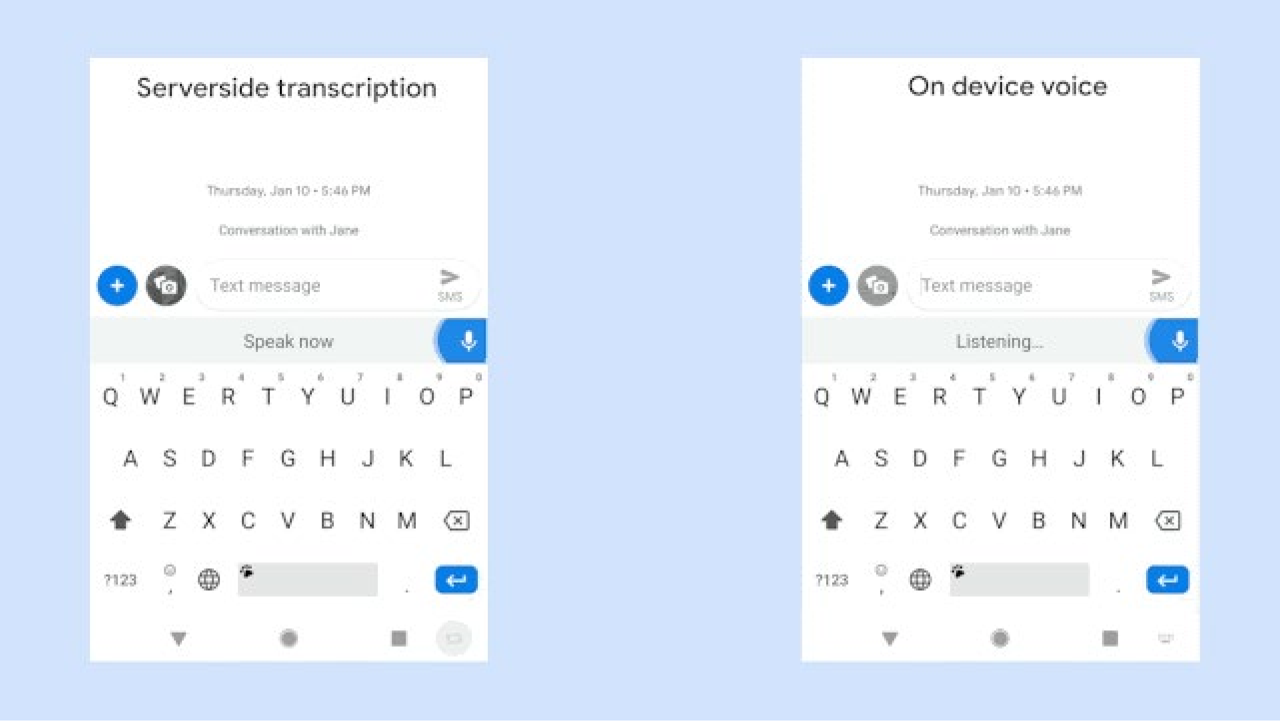
[Sainath et al., 2020]

Model	Size	VoiceSearch Word Error Rate (%)	EOU Latency (90 percentile)
Conventional Server	0.1GB (AM) + 2.2 GB (PM) + 4.9 GB (LM) + 80 GB (2nd-pass LM) = 87.2 GB	6.6%	870ms
On-device End-to-End	**0.18 GB**	**6.1%**	**780ms**

“ You can ask Assistant to do things that are **local to your phone**, and they'll happen **near instantaneously**...it is much faster and needs to rely on Google's server **much less**. ”

The Verge: [Google Pixel 4 and 4 XL Hands-on: this time, it's not about the camera.]

Gboard Demo


Serverside transcription
Thursday, Jan 10 • 5:46 PM
Conversation with Jane
Text message
SMS
Speak now
On device voice
Thursday, Jan 10 • 5:46 PM
Conversation with Jane
Text message
SMS
Listening...

- **Summary:**
  - Attention-based End-to-End models (LAS) **achieves state-of-the-art performance**, but is **not streaming**.
  - Recurrent Neural Network Transducer (RNN-T) provides an **accurate** and **fast on-device** speech recognition experience.
  - RNN-T EP + 2nd-pass LAS **surpasses** server-side conventional model in both **quality** and **latency**.

- **Challenges:**
  - Dealing with long tail words.
  - Further simplify the ASR system to build a single End-to-End model for multiple languages.

2021 On-Device Improvements

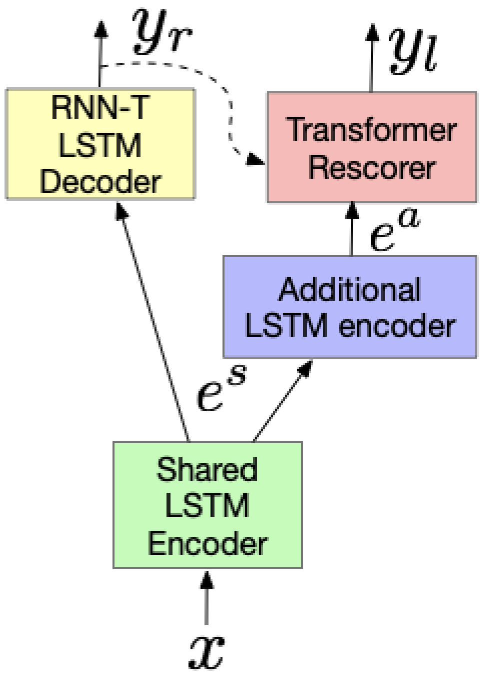
2021 End-to-End Goals with Pixel 6

Our goals in Pixel 6 are to develop an **on-device** end-to-end model that

- **Surpasses quality** (as measured by word error rate) of a conventional server-based model, on both general search traffic and long-tail phrases
- Is **faster** in terms of **latency** (endpointer, computational) compared to server-based model
- Consumes **lower power** than Pixel 4 / 5 for both short and long form audio.

Pixel 4/5 Model

- Model Details
  - 105M param LSTM Encoder
  - 20M param LSTM Decoder
  - 54M Transformer Rescorer + Additional LSTM Encoder
  - Model trained only on multidomain audio-text pairs



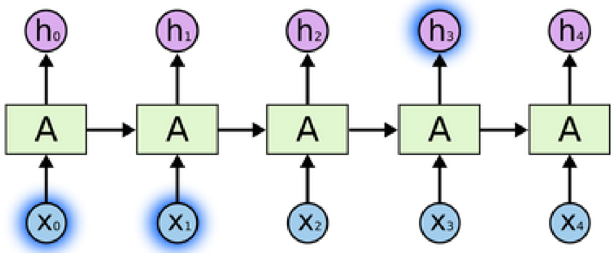
Pixel 6 Specifications

- Pixel 6 Google Tensor SoC Hardware
  - Google Tensor on-device edge TPU
  - 8 CPU cores
  - 8G (Pixel 6) or 12G (Pixel 6 Pro) DRAM
- We want an architecture where
  - **Encoder** can be **parallelized**
    - LSTM encoder → conformer encoder
  - **Decoder** that can **small** enough fit into SRAM
    - LSTM decoder → embedding decoder
  - **2nd-pass** is **streaming** for long-form
    - Transformer Rescorer → Multi-rate encoders
  - Does well on **long-tail named entities**
    - Additional Conformer Language Model

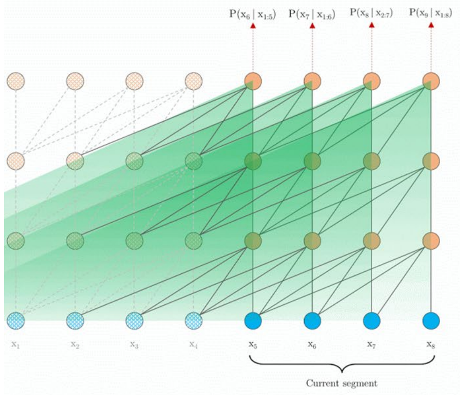
Latency Improvement: LSTM Encoder → Conformer Encoder

[Gulati et al, 2020][Zhang et al., 2020]

- LSTM
  - Sequential time dependency → not TPU friendly
  - Deletions in Long-form due to time dependency



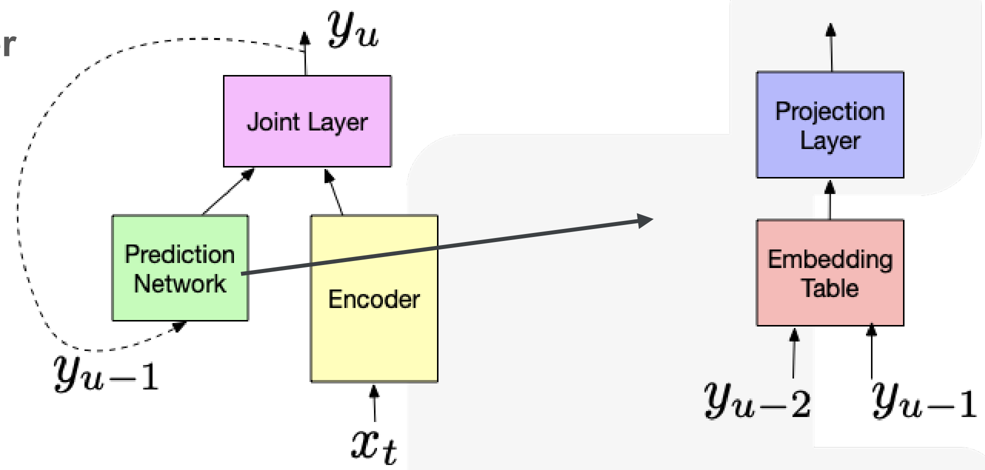
- Conformer/Transformer
  - Can compute multiple activations in parallel → more TPU friendly
  - Deletion issue less of a concern



Latency Improvement: LSTM Decoder→ Embedding Decoder

[Variani et al, 2020][Botros et al., 2021]

- Motivation:
  - Bottleneck of TPU is the **latency transfer** of parameters between CPU and SRAM on the TPU
  - If decoder is small enough, it can fit inside local SRAM on TPU
- Replace the LSTM decoder (33M params) with a simple embedding decoder lookup table (~2M params)
- This gives **~30% computation speedup** with no accuracy degradation

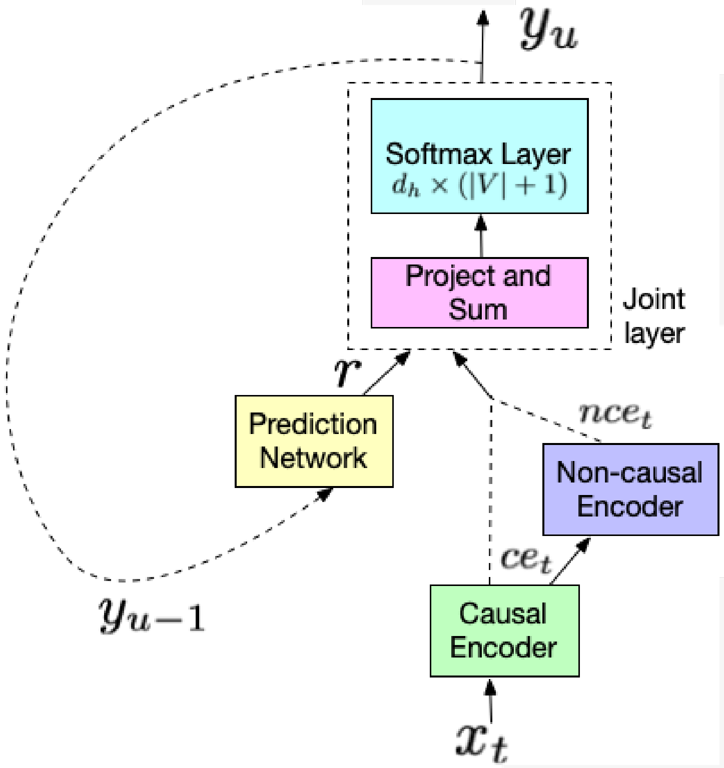


Quality Improvement: Multi-rate Encoders

[Tripathi et al, 2021][Yu et al., 2021][Narayanan et al., 2021]

- Segment and rescore (Pixel 5 architecture)
  - Not ideal for long-form
  - Beam search is better then rescoring

- Multi-rate encoders (Cascaded encoders)
  - 1st-pass causal encoder →decoder
  - 2nd-pass additional non-causal layers → decoder
  - Quality improvement with beam search while still being able to run in real time



Quality Improvement: Neural Language Model

[Variani et al, 2020]

- Incorporate Hybrid Autoregressive Transducer (HAT) factorization to better integrate language model

$$y^* = \arg\max_y \left[\log p(y|x) - \lambda_2 \log p_{ILM}(y) + \lambda_1 \log p_{LM}(y)\right]$$

- Language models:
  - Perform shallow fusion with a contextual biasing FST
  - Perform rescoring with a conformer LM trained on ~100 billion text utterances. This helps to address the long-tail proper noun issue.

ASR | WER for Short Form: en -US General Test Sets

[Sainath et al, 2021]

NGA: en-US with Conformer Cascaded Encoder + Neural LM is the best ASR we have built

Test Set / Vertical (en_us)	Server WER [Classic]	Pixel 4/5 WER [LSTM]	Pixel 6 WER [Conformer]
VS (Voice Search)	7.3	6.0	5.6
2018_VS	7.5	6.9	6.4
VS_NOISY	9.6	9.9	8.2
NUMERIC	5.7	5.4	5.2
VA_PLANNING	4.2	4.4	3.1
ASSISTANT_ON_ANDROID	6.8	8.0	5.9

ASR | WER for Short Form: en-US Biasing Test Sets

[Zhao et al, 2019]

- Biasing is an attempt to adapt the priors baked into the speech models to better model information gained between training and inference (aka context)
- Common uses cases include contacts, media and apps

Vertical / Use Cases	Server WER [Classic] w/ biasing (w/o biasing)	Pixel 4/5 WER [LSTM] w/ biasing (w/o biasing)	Pixel 6 WER [Conformer] w/ biasing (w/o biasing)
Contacts	9.7 (17.2)	6.1 (15.5)	3.3 (14.0)
Media	7.2 (7.8)	4.2 (9.1)	3.5 (8.7)
Open Apps	6 (6.1)	3.5	2.6 (5.0)

Biasing on conformer models further accelerated the quality improvements across verticals

ASR | Quality Wins on SxS Live Traffic

SxS: Live voice search queries are recognized by both on-device conformer and server. Then both results are sent to human raters for comparison. The on-device conformer model has cascaded encoder and neural LM rescorer.

On-device Conformer vs Server (SxS)				
Win	Loss	Neutral	p-Value	Impact
120	36	334	<0.1%	5.7e-2

Win/Loss ratio: 120 / 36 , which means new model is much better than current server model

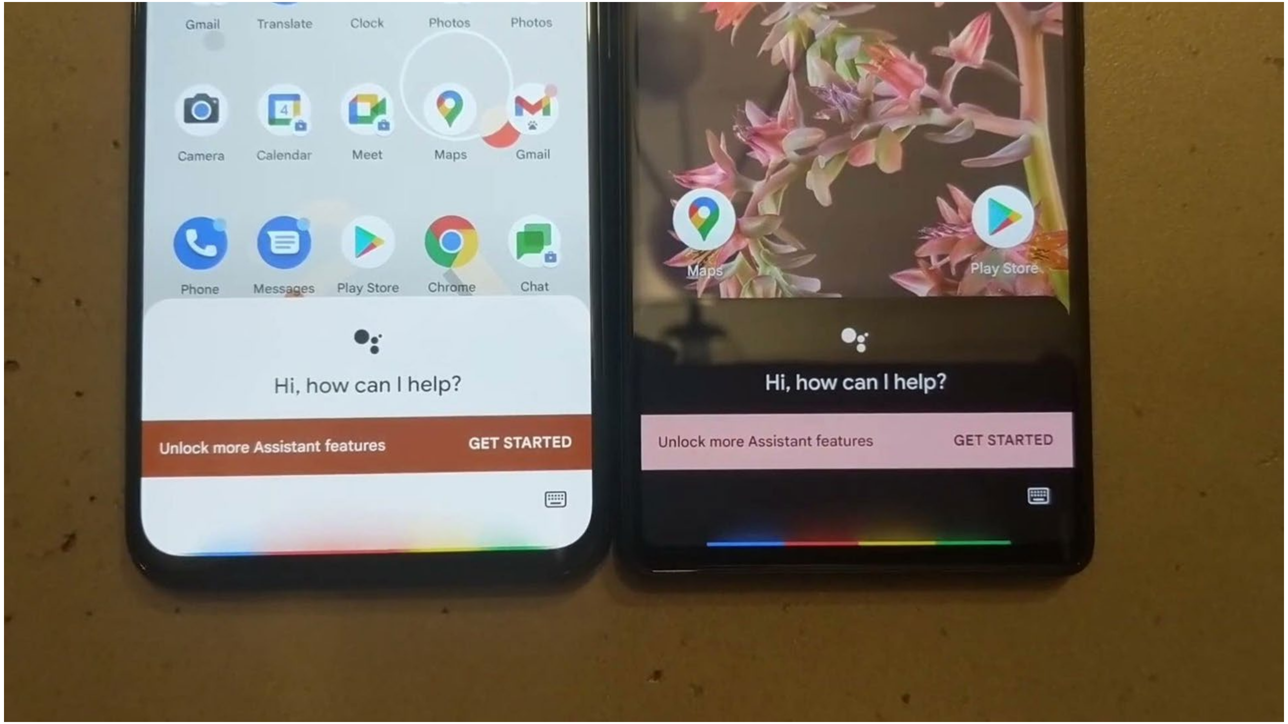
Video on Rare Words

Pixel4 (RNN-T + Transformer Rescorer)

X Bear County Texas

Pixel6 (Conformer + Cascade Encoder + Neural LM)

✓ Bexar County Texas



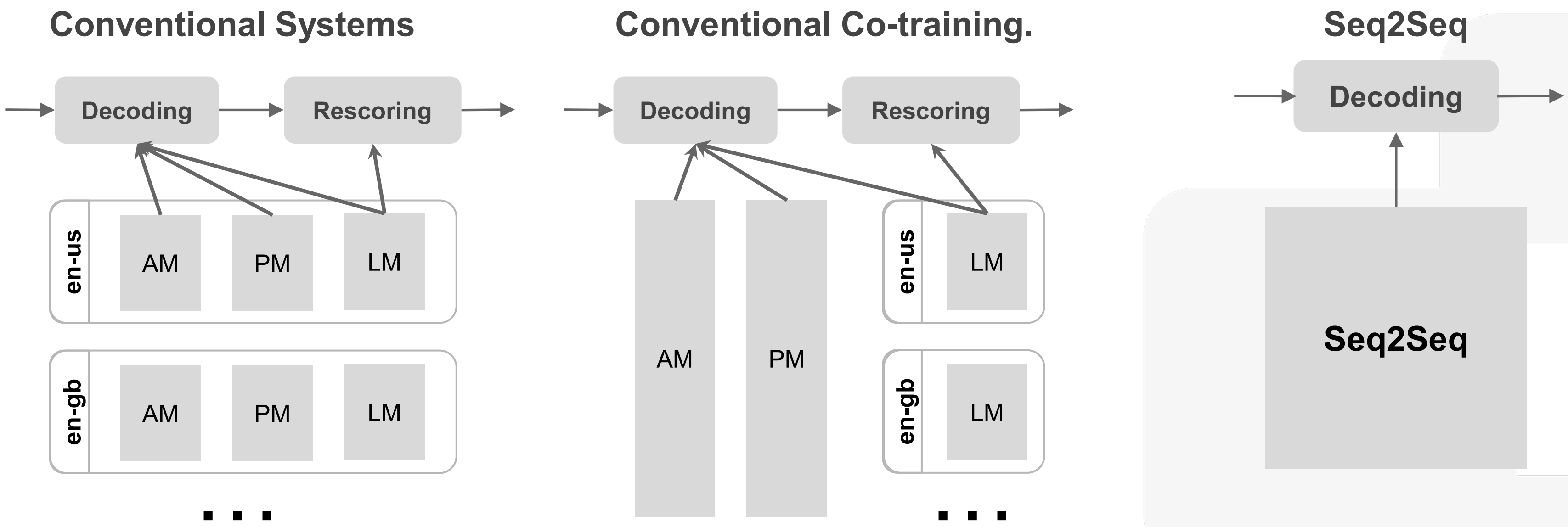
Pixel 6 Video

- **Summary:**
  - Attention-based End-to-End models (LAS) **achieves state-of-the-art performance**, but is **not streaming**.
  - Recurrent Neural Network Transducer (RNN-T) provides an **accurate** and **fast on-device** speech recognition experience.
  - [Pixel 4/5] RNN-T EP + 2nd-pass LAS **surpasses** server-side conventional model in both general search **quality** and **latency**.
  - [Pixel 6] Cascaded Encoder + neural LM **surpasses** server-side conventional model and Pixel 4/5 in both general search and long-tail **quality** and **latency**.

Future Challenges

E2E multi-dialect ASR

[Li et al., 2018, Toshniwal et al, 2018]



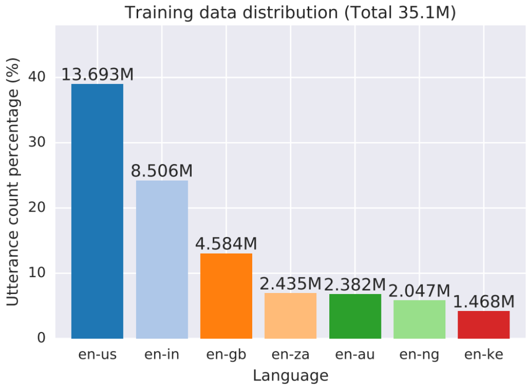
In conventional systems, languages/dialects, are handled with **individual AMs, PMs and LMs**. Upscaling is becoming challenging.

A single model for all.

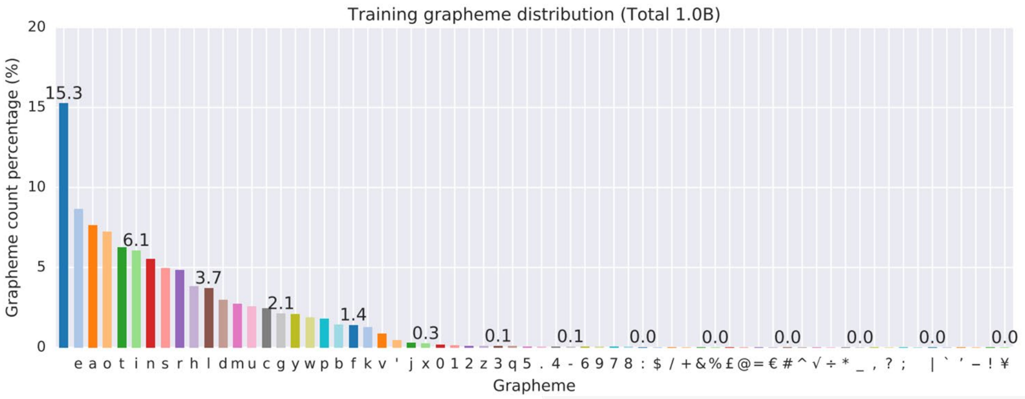
Task

[Li et al., 2018]

- **7 English dialects:** `US (America), IN (India), GB (Britain), ZA (South Africa), AU (Australia), NG (Nigeria & Ghana), KE (Kenya)`



★ **unbalanced** dialect data



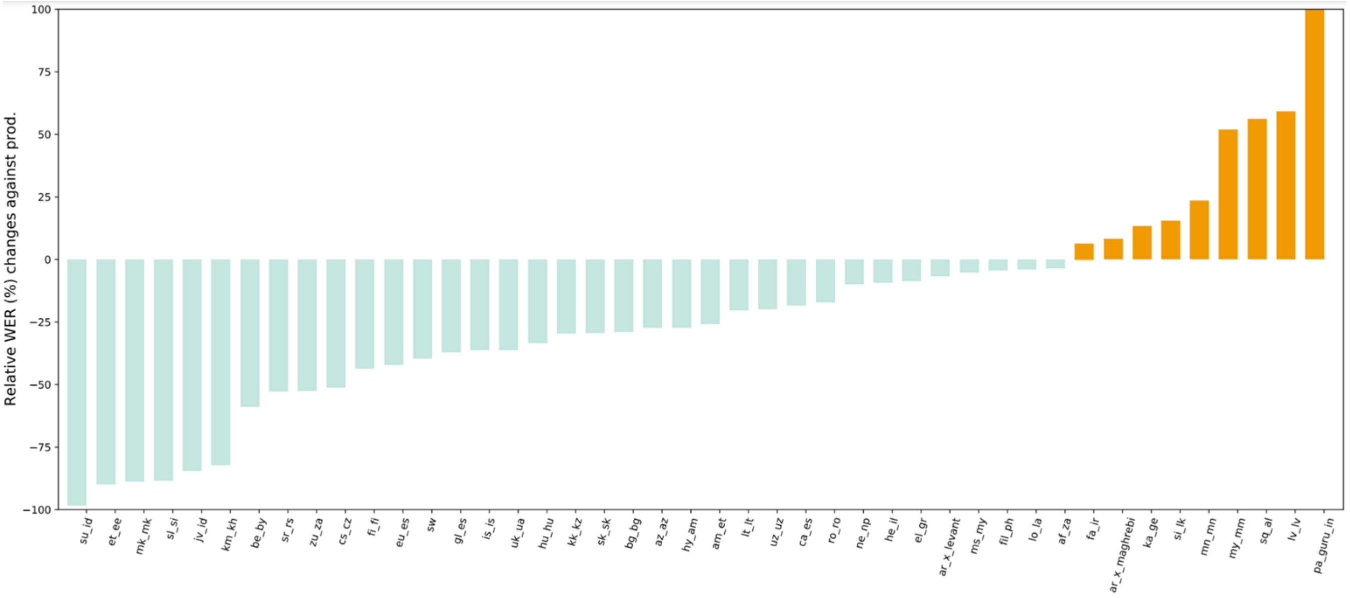
★ **unbalanced** target classes

E2E With Dialect as Input Features

Dialect	US	IN	GB	ZA	AU	NG	KE
Baseline (dialect-dep.)	9.7	16.2	12.7	11.0	12.1	33.4	19.0
encoder	9.6	16.4	11.8	10.6	10.7	31.6	18.1
decoder	9.4	16.2	**11.3**	10.8	10.9	32.8	18.0
both	**9.1**	**15.7**	11.5	**10.0**	**10.1**	**31.3**	**17.4**

★ feeding dialect to **both encoder and decoder** gives the largest gains

Question : Can we train **one model** on 44 low-resource languages?



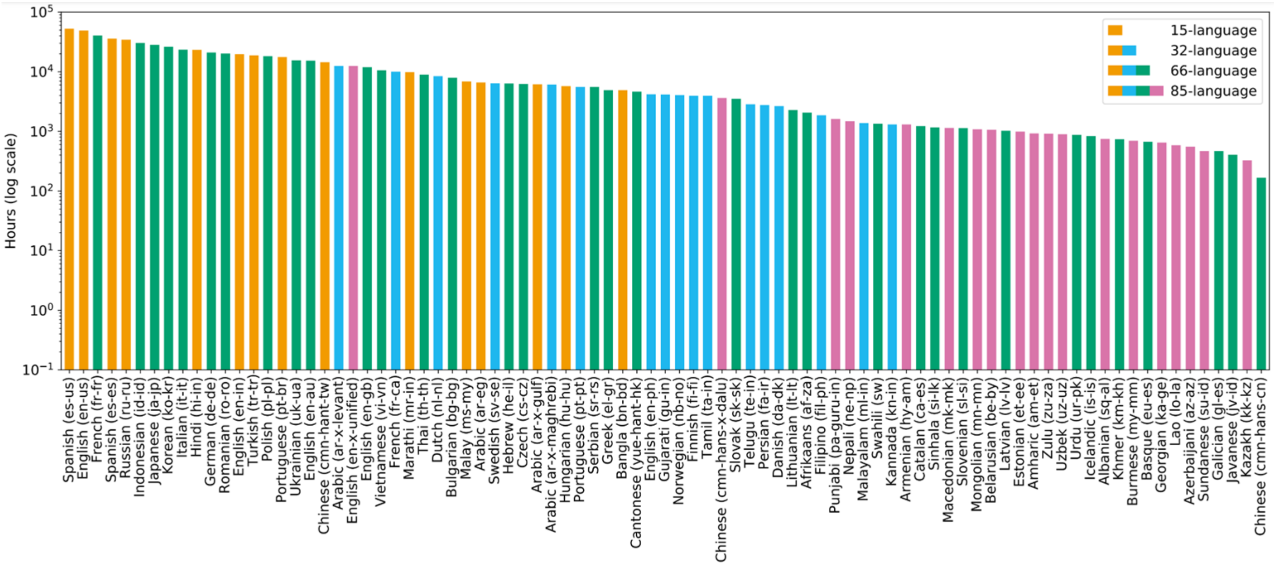
Key Result : Comparing to E2E trained on each individual language, 1 MMASR E2E model **wins** over **35 languages** .

Cross-lingual sharing boosts quality.

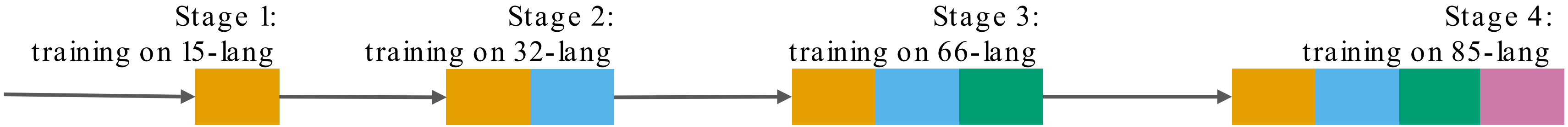
Infrastructure **simplified** with one model.

Task

Building **high quality** teacher models across languages.



With a fixed 1B-param model size, **lifelong learning** resolves the quality regressions.



Exp.	en-us	Avg. WER(%)			
		15-lang	32-lang	66-lang	85-lang
Monolingual	4.6	9.3	11.9	-	-
Training from scratch	5.4	10.4	13.3	11.5	12.3
Lifelong learning	**4.2**	**8.8**	**11.5**	**9.9**	**10.9**

[1] Massively Multilingal ASR: A Lifelong Learning Solution

Research Challenges

- How can we scale multi-lingual E2E for more languages?
- How can we maintain quality when the model is not fed a language-id?
- How do we handle code-switching within the utterance?
- How can we do this at an appropriate model size for on-device?

Thank You

Google

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