Improving performance of Transformer based Low Resource Speech Recognition for Indian Languages

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Objective

Address the Speech Recognition problem of Low Resource Indian Language using Transformers

Explore different ways of incorporating language information

- At character level.
- At acoustic feature level.

Our method of providing language information at feature level gave the best recognition performance.

Transformers in Speech Recognition

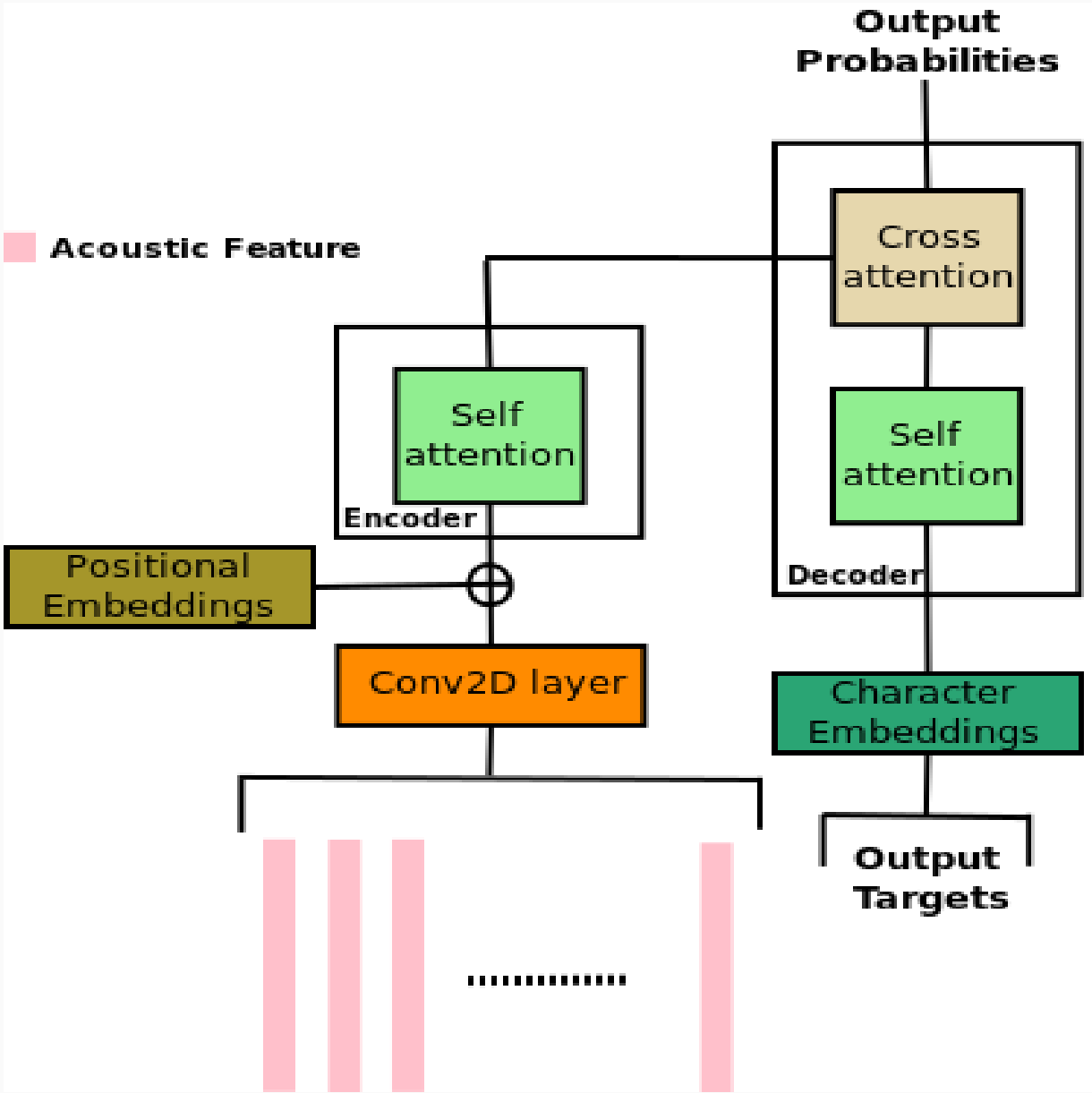
Transformers in ASR

Transformer

- An E2E framework based solely on attention.
- It comprises of a series of ”Attention” (Self/Cross) and ”Feed forward networks”
- Have shown promising results in several NLP tasks.

This has motivated its application to Automatic Speech Recognition.

Transformers in ASR



Dataset Details

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Language		Train	Dev	Eval
Gujarati	Dur(hrs)	40	5	5
	# Utter	22807	3075	3419
Tamil	Dur(hrs)	40	5	5
	# Utter	39131	3081	2609
Telugu	Dur(hrs)	40	5	5
	# Utter	44882	3040	2549

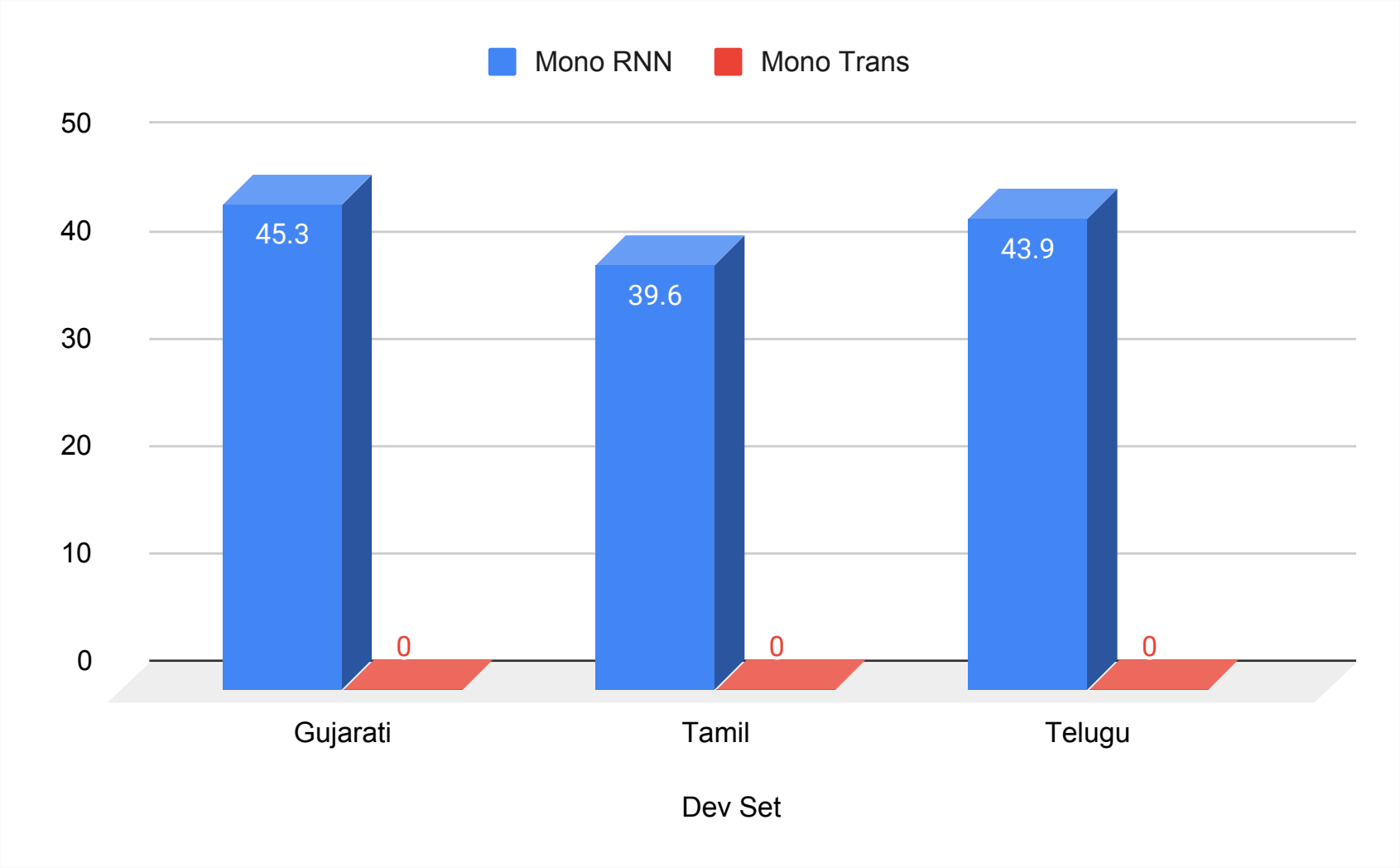
Transformers versus RNNs

Transformers versus RNNs

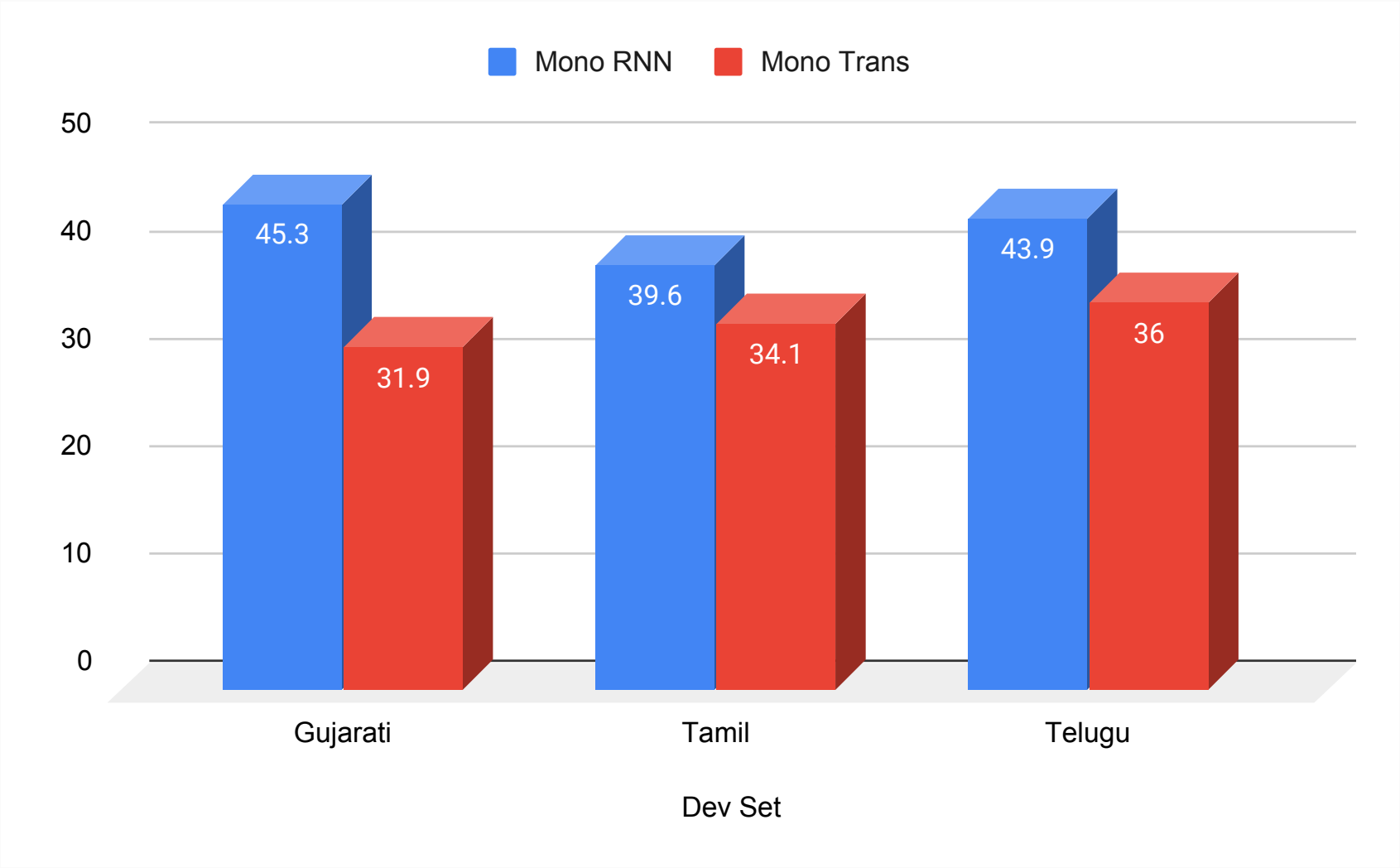
Models were trained based on Hybrid CTC/Attention approach using ESPNET tool on GTX 1080 GPU.

- RNN based model:
  - Four layer encoder with 320 BLSTM units
  - One layer decoder with 300 LSTM units
  - ”Location” aware attention was used
  - Multi-task learning co-efficient - 0.5
- Transformer model
  - Twelve layer encoder with 2048 units
  - One layer decoder with 1024 units
  - Attention dimension of 256
  - Multi head attention with four attention heads
  - Multi-task learning co-efficient - 0.3

Transformers versus RNNs



Transformers versus RNNs



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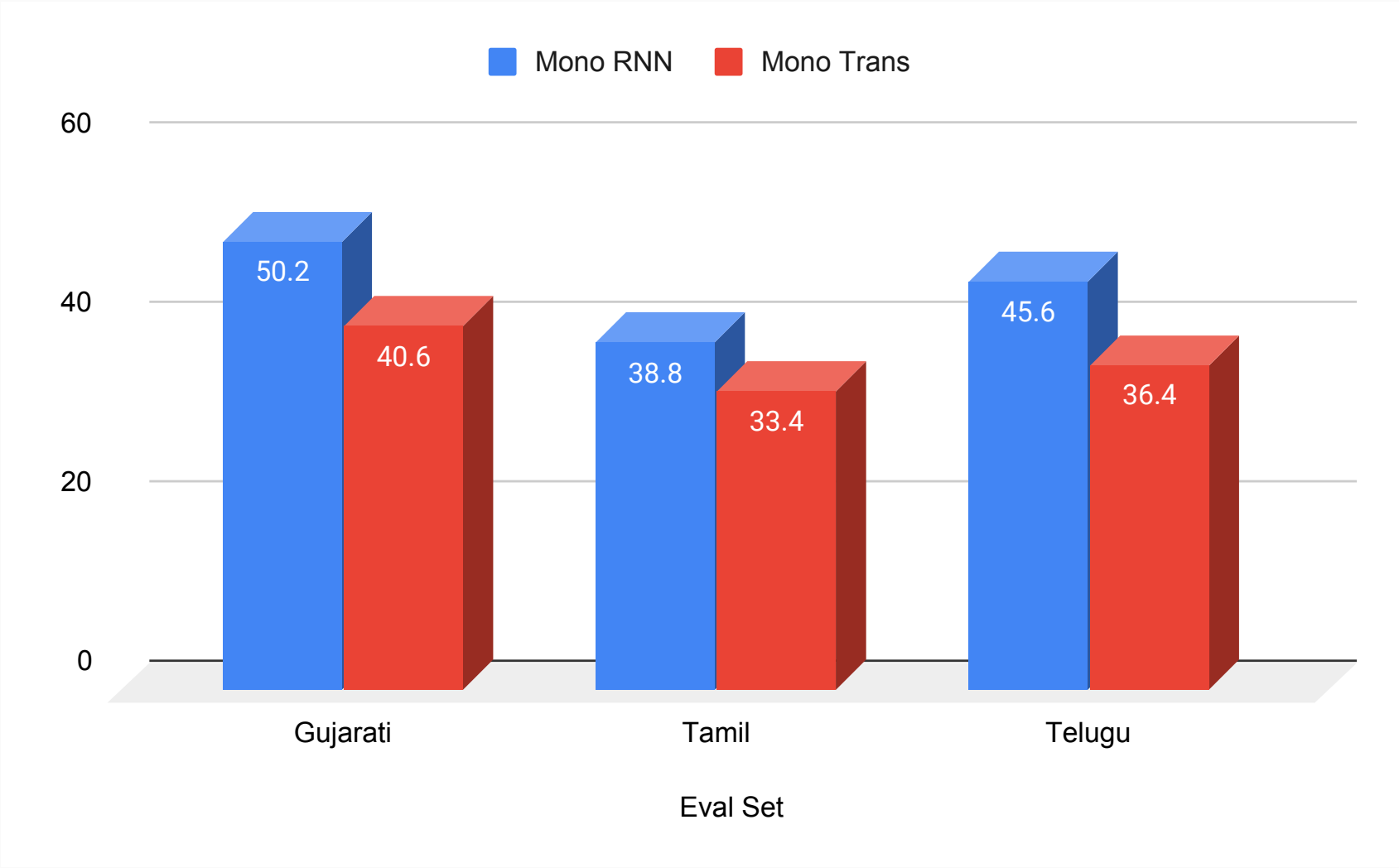


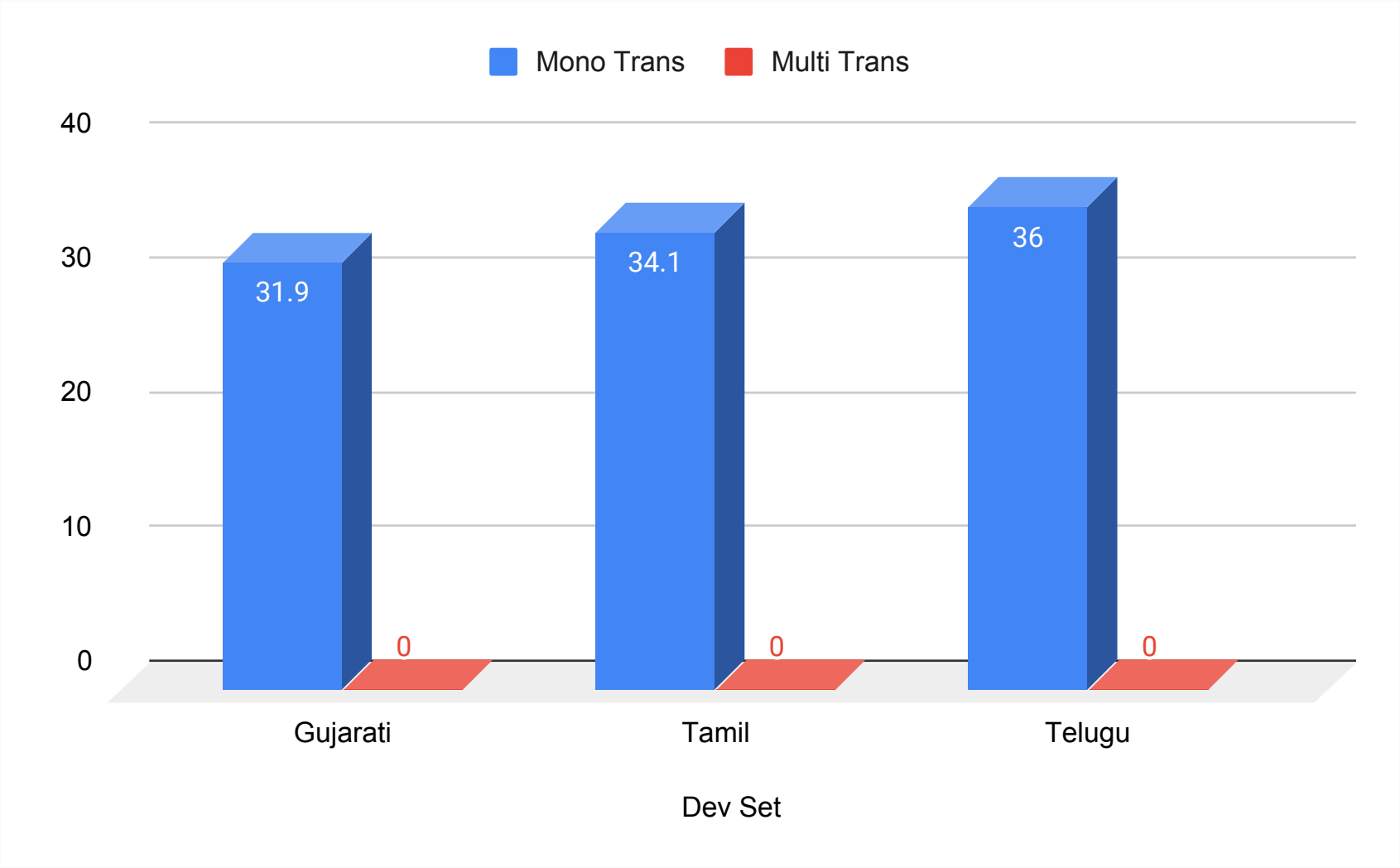
Can we do better than this?

Multilingual Models - Pool data from all the languages

- Build one single model by combining data from all the languages.
- The target character set is the union of characters from individual languages - 64 Guj, 48 Tam and, 64 Tel

Language	Transcript
Gujarati	મેટ્રો રેલનું કામ
Tamil	பிரதமர் மன்மோகன் சிங்
Telugu	ఆంధ్రప్రదేశ్ రాజధాని అమరావతికి

Multilingual Model – Pooled data



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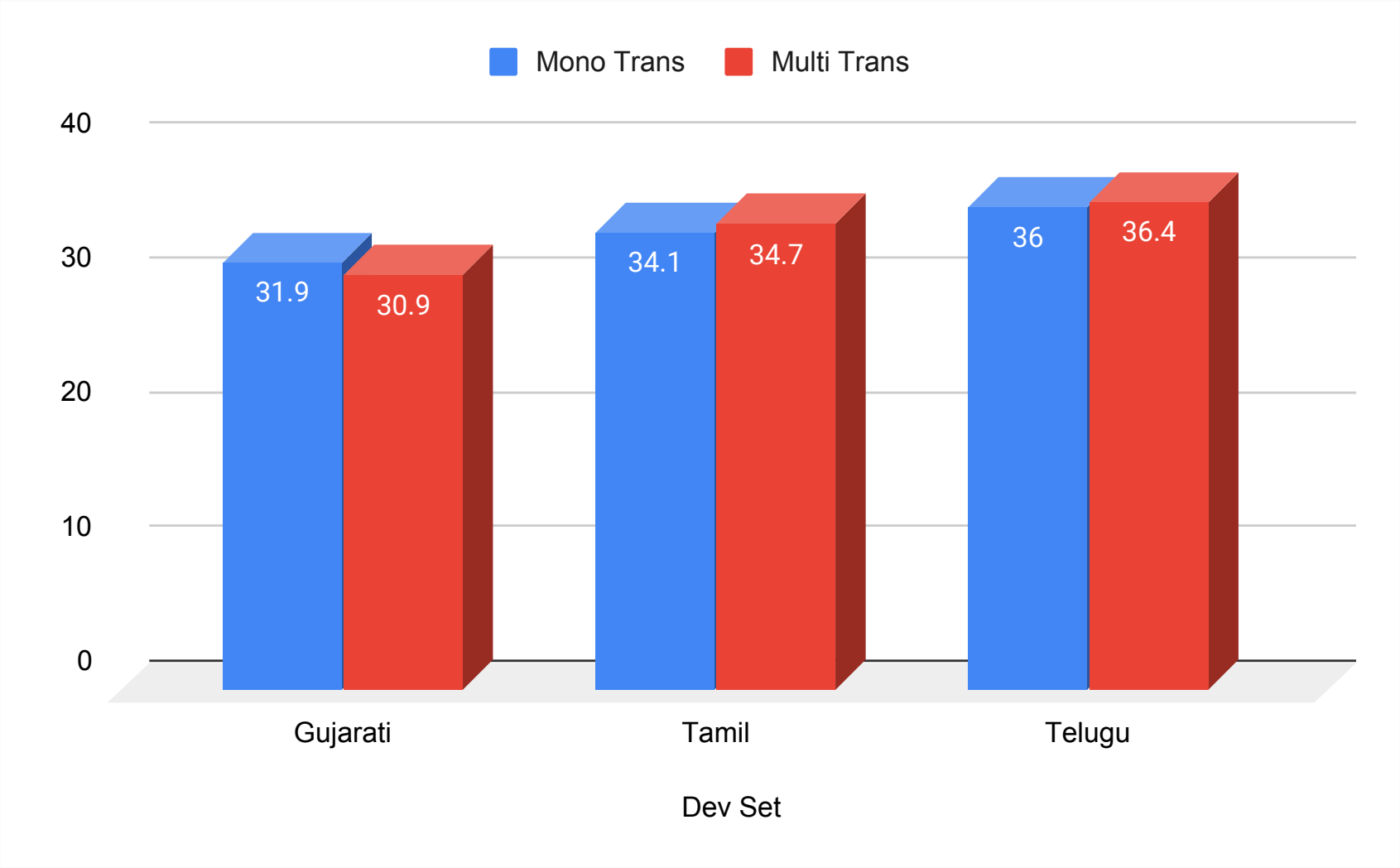
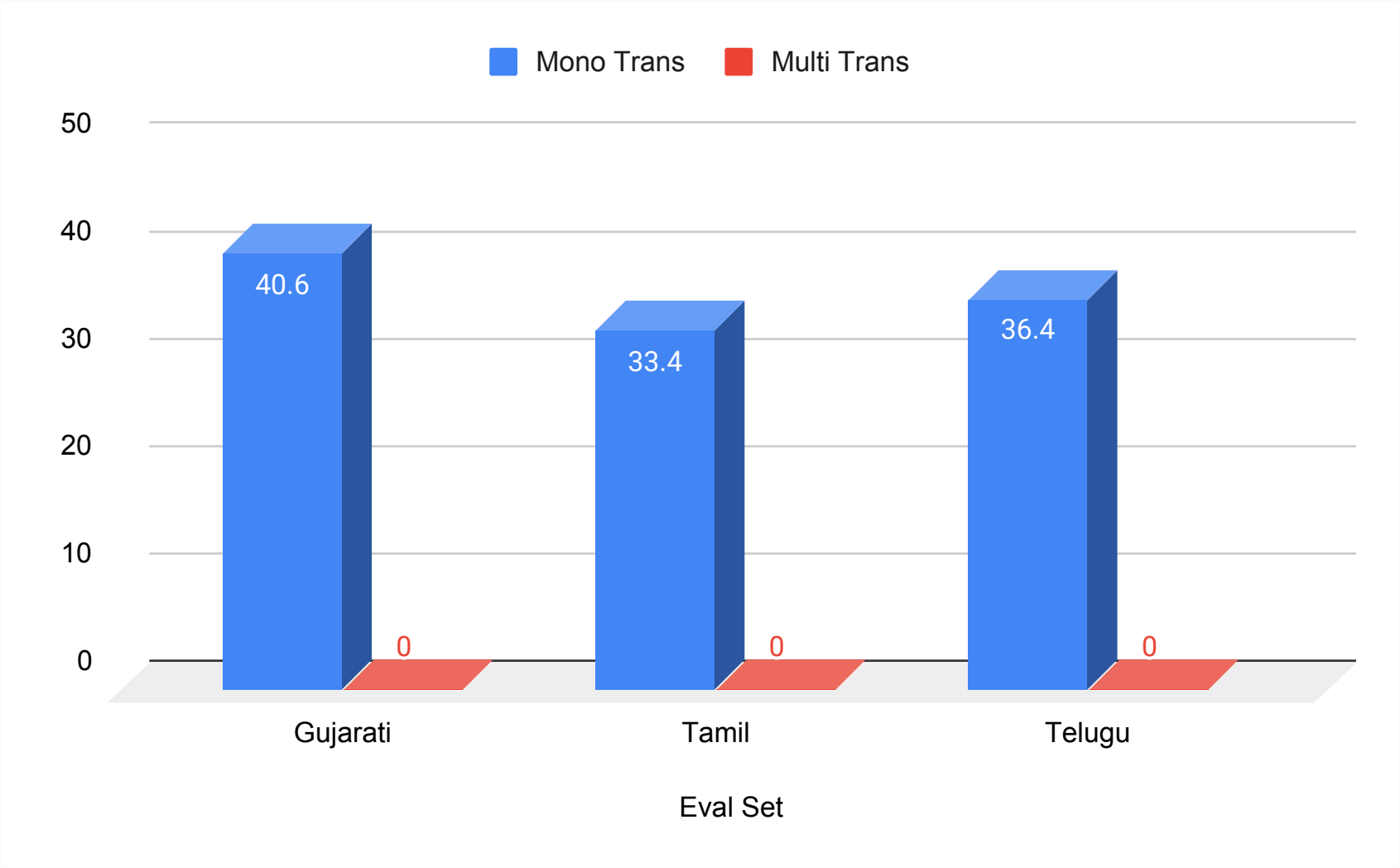


Multilingual Model – Pooled data



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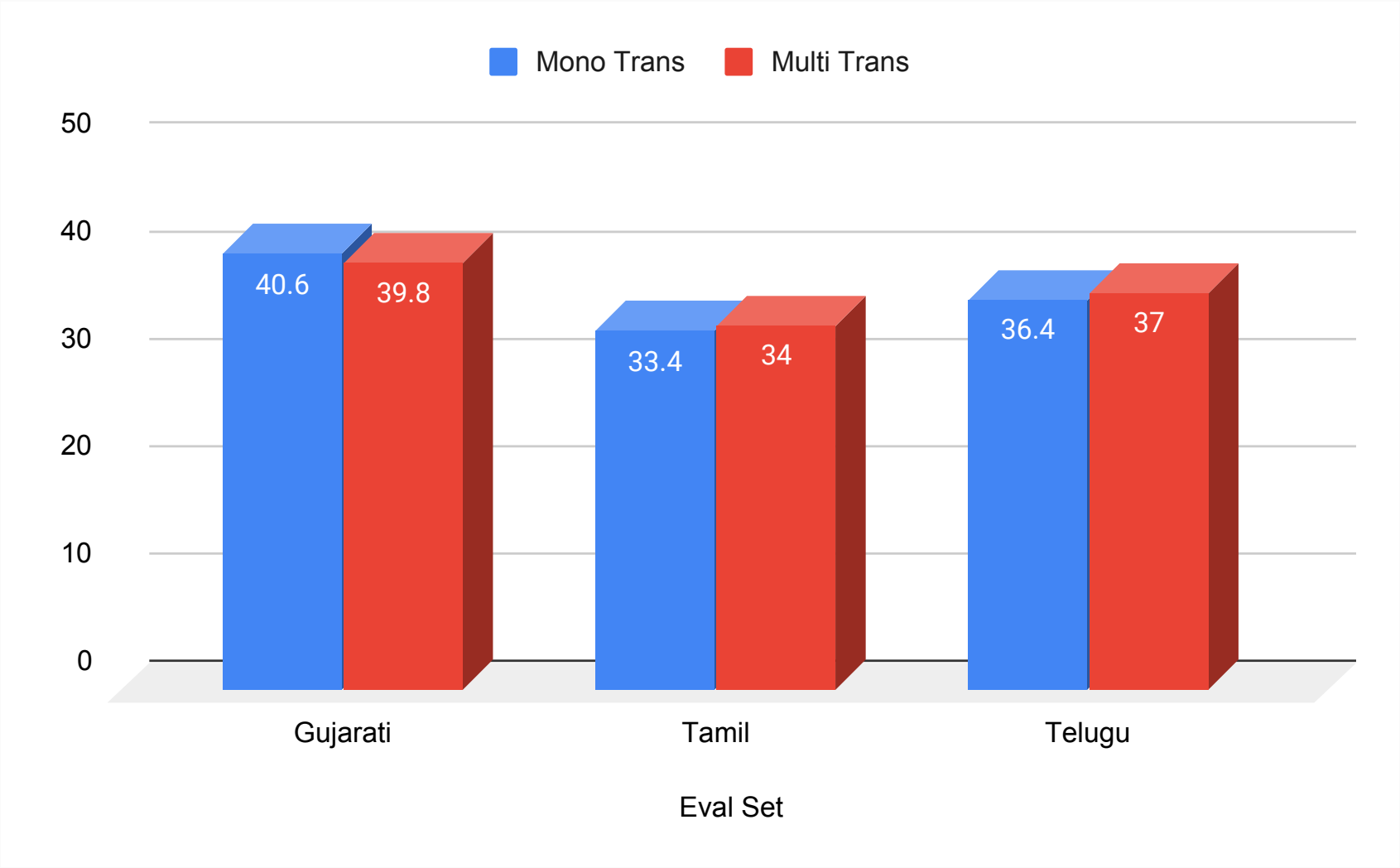


Can we make use of the language information?

Two possible Strategies

Assuming Language information known during training:

- Provide language information at the decoder –character level
- Provide language information at the encoder –feature level

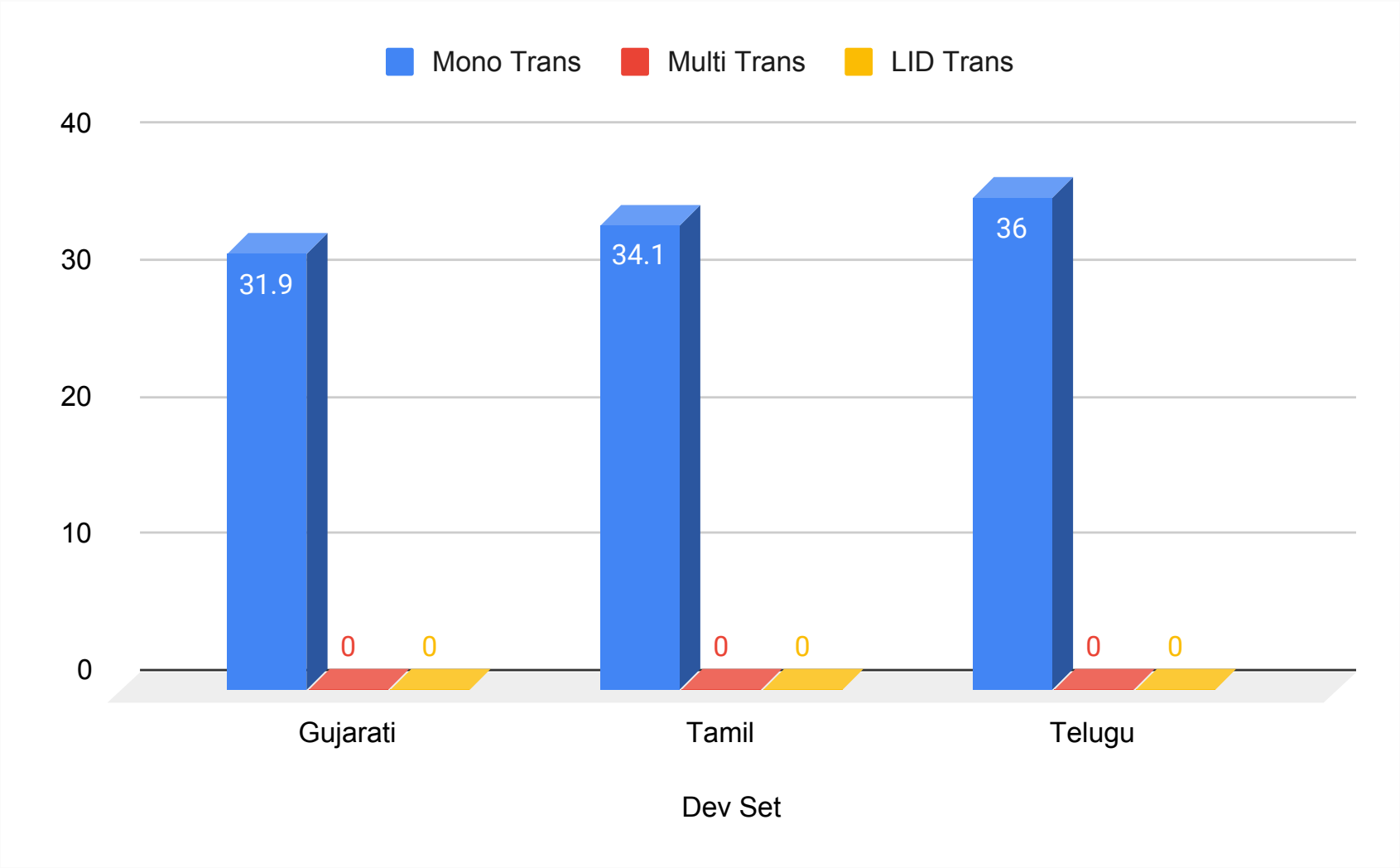
Strategy 1: Provide Language information at the decoder

Language	Example
Gujarati	<guj_beg> આતંકી હુમાલો હુમલો <guj_end>
Tamil	<tam_beg> கண்டிப்பா கண்டிப்பா <tam_end>
Telugu	<tlg_beg> అనంతరం <tlg_end>

Table 1: Examples of LID in the target sequence

No LID used during testing – Hence Universal Speech recognizer.

Strategy 1: Provide Language information at the decoder



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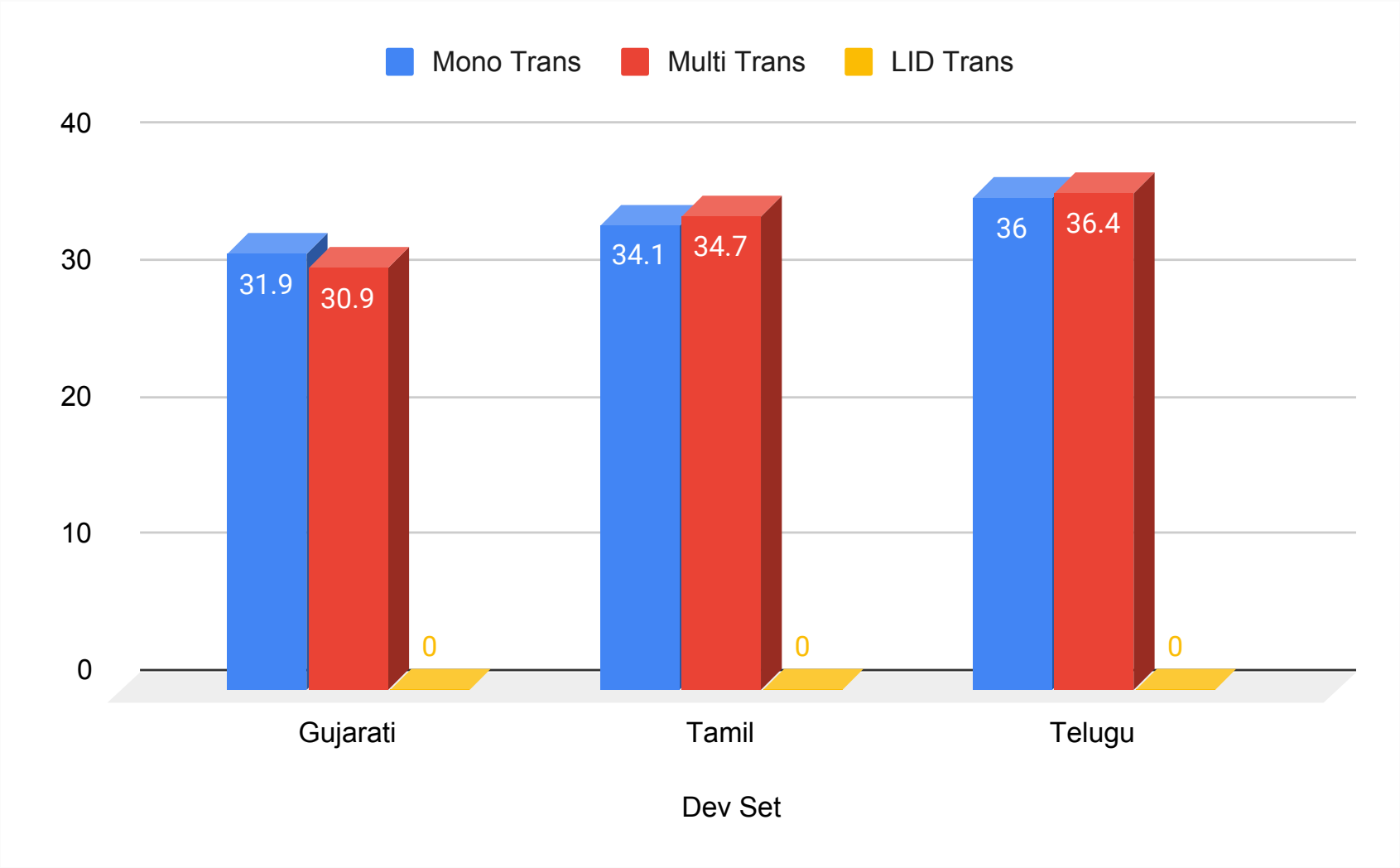

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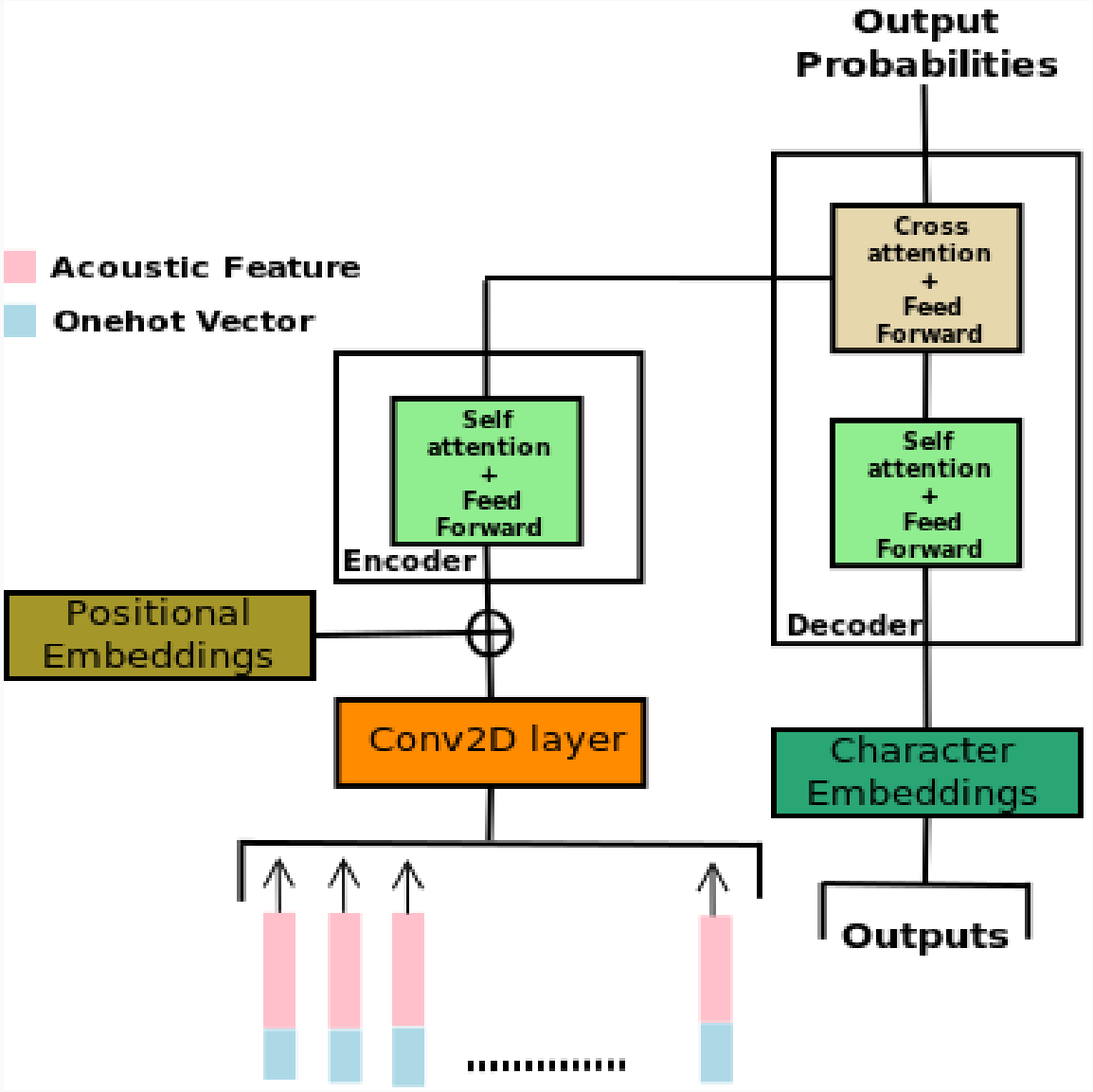
Strategy 2: Language information at the encoder

Provide language information at feature level:

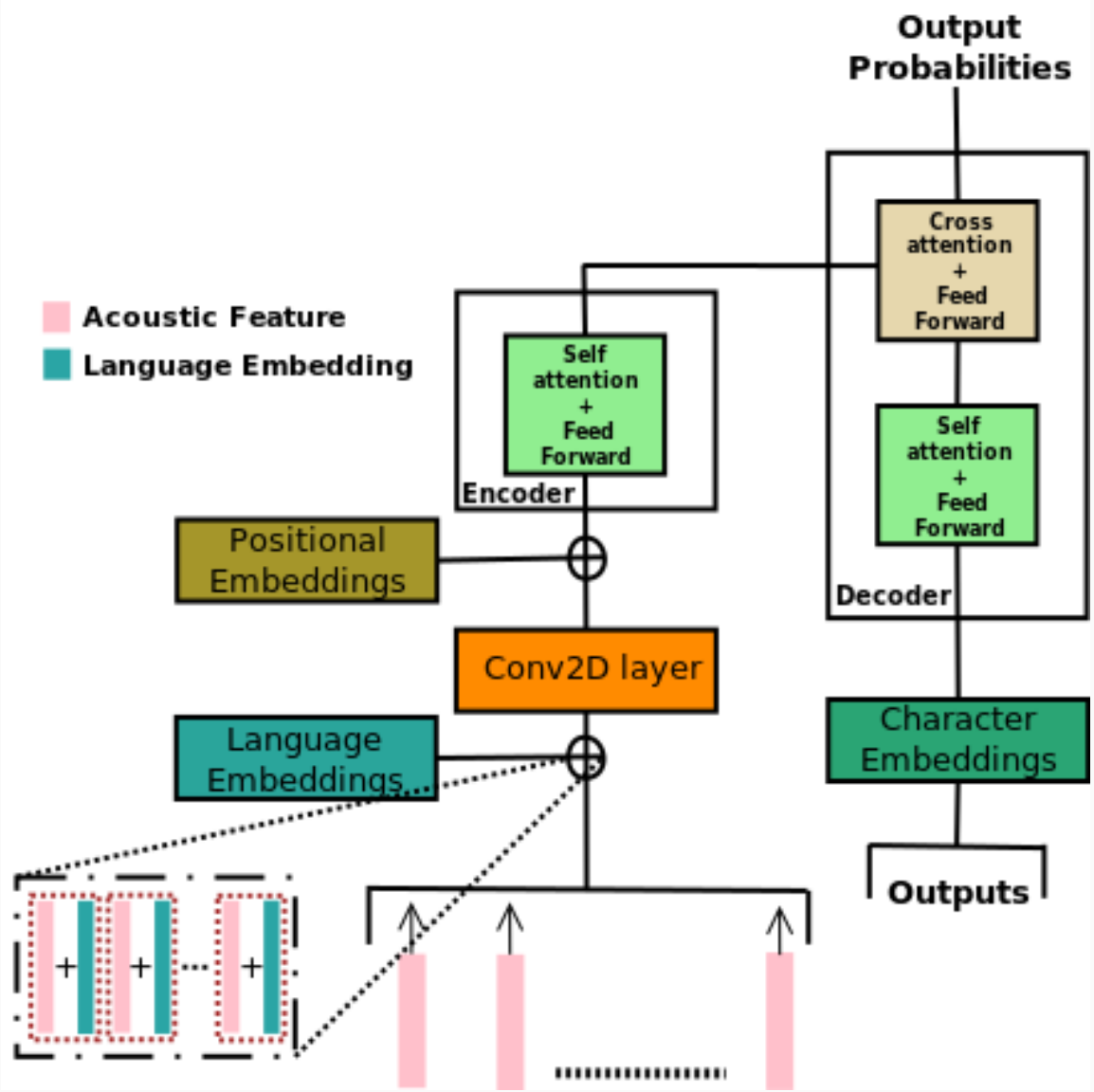
- Append one hot vector
- learn feature embeddings for the language

Language information is used while decoding, hence these models are **Language Specific Models**

Strategy 2a: Appending One hot vector



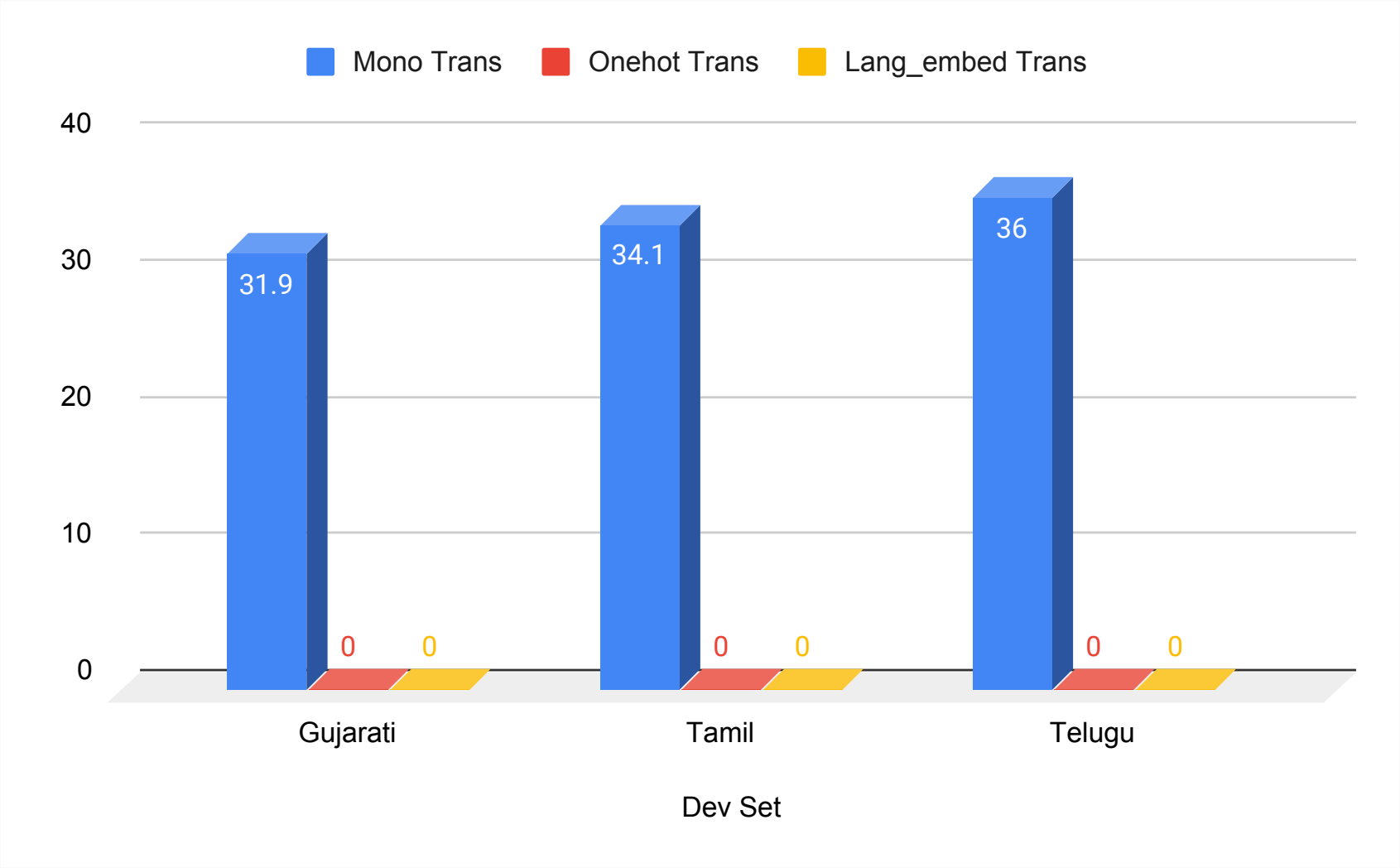
Strategy 2b: Learning Language embedding



Strategy 2b: Learning Language embedding

- Analogous to how Character Embedding is learnt at the decoder
- Embedding vectors are initialized to a random vector with the dimension of acoustic feature
- Given an utterance - the targets belong to only one language - this information is used

Strategy 2: Results



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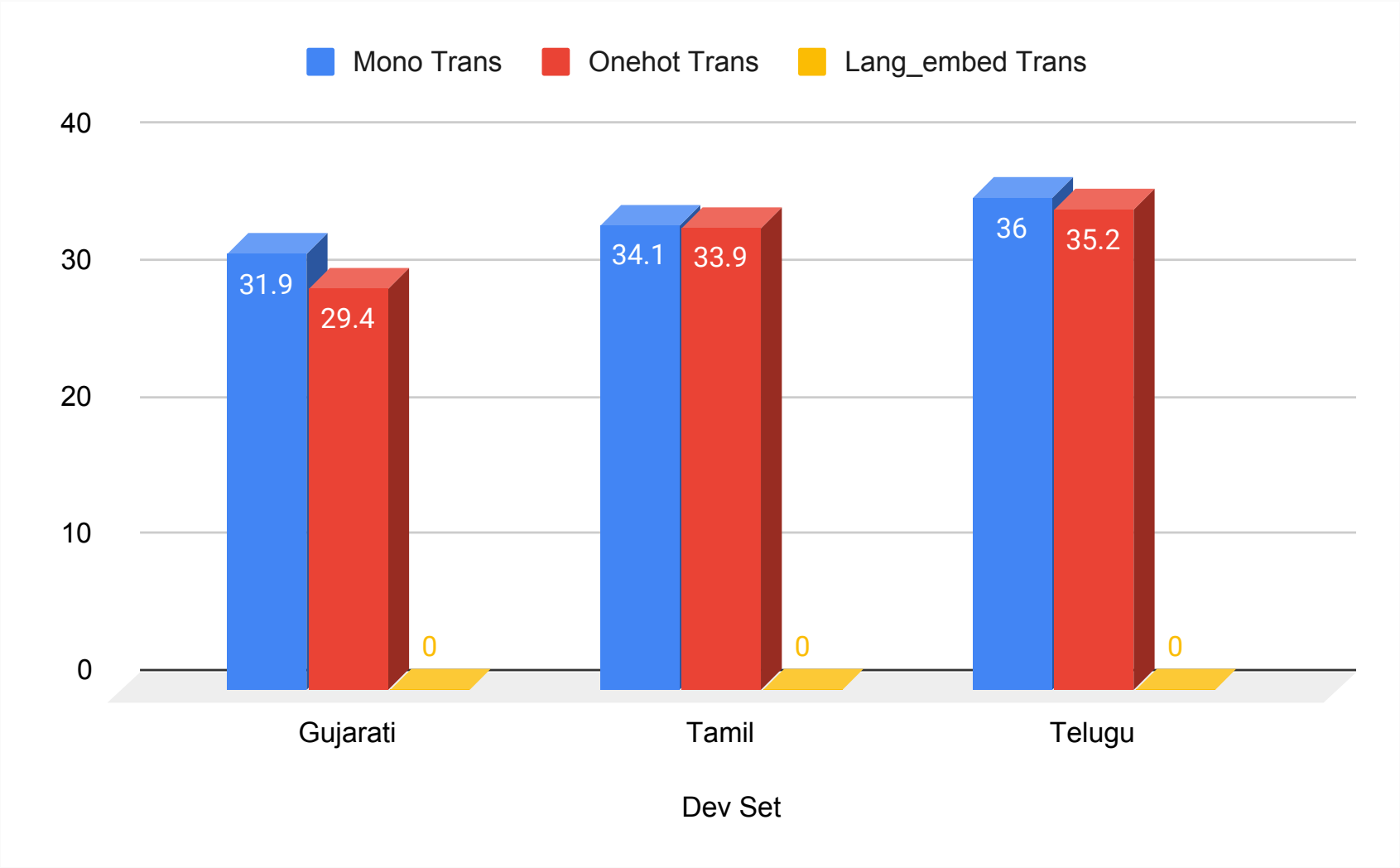

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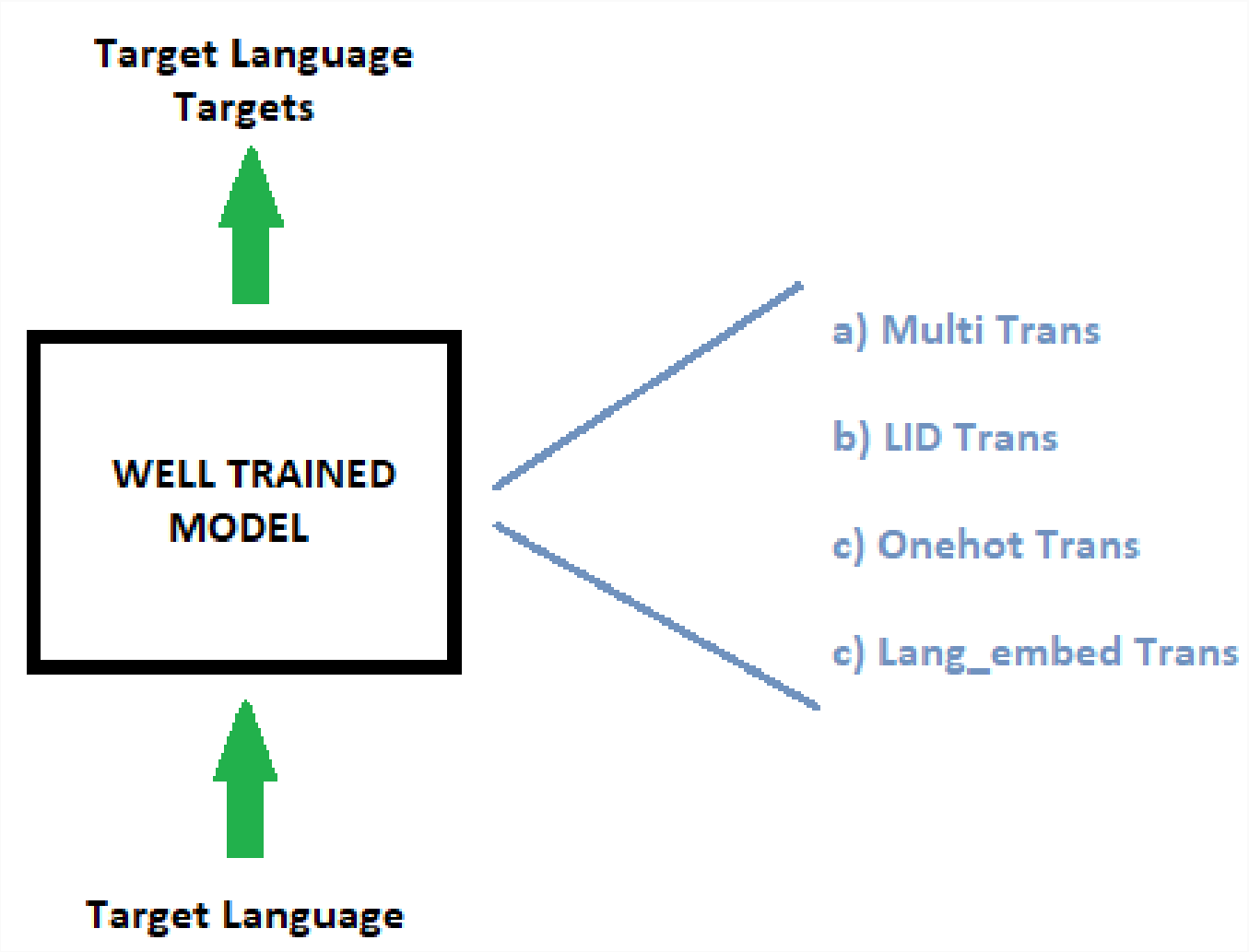
Fine tuning

Fine tuning

Retrain well trained model using the target language



Results after retraining

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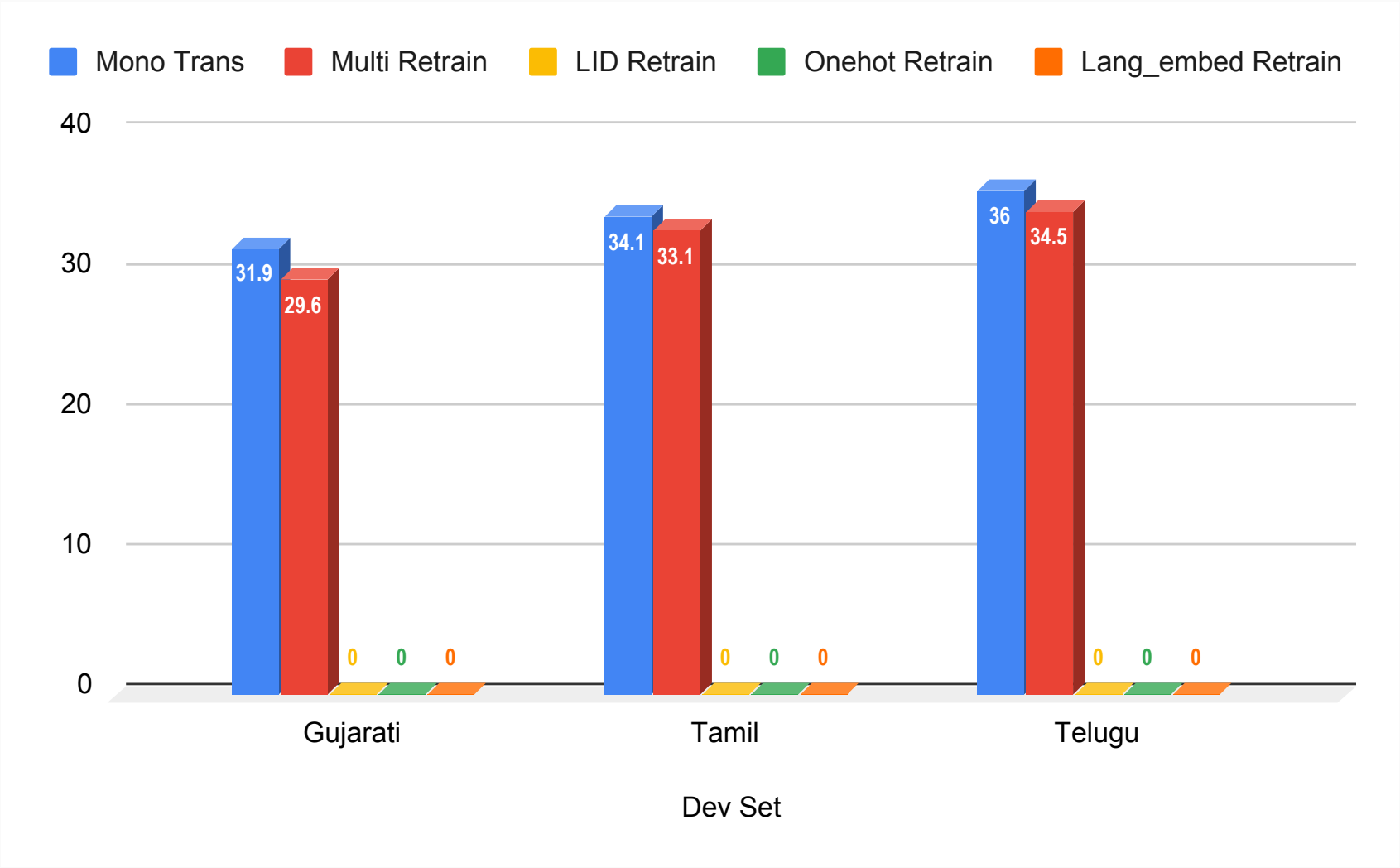

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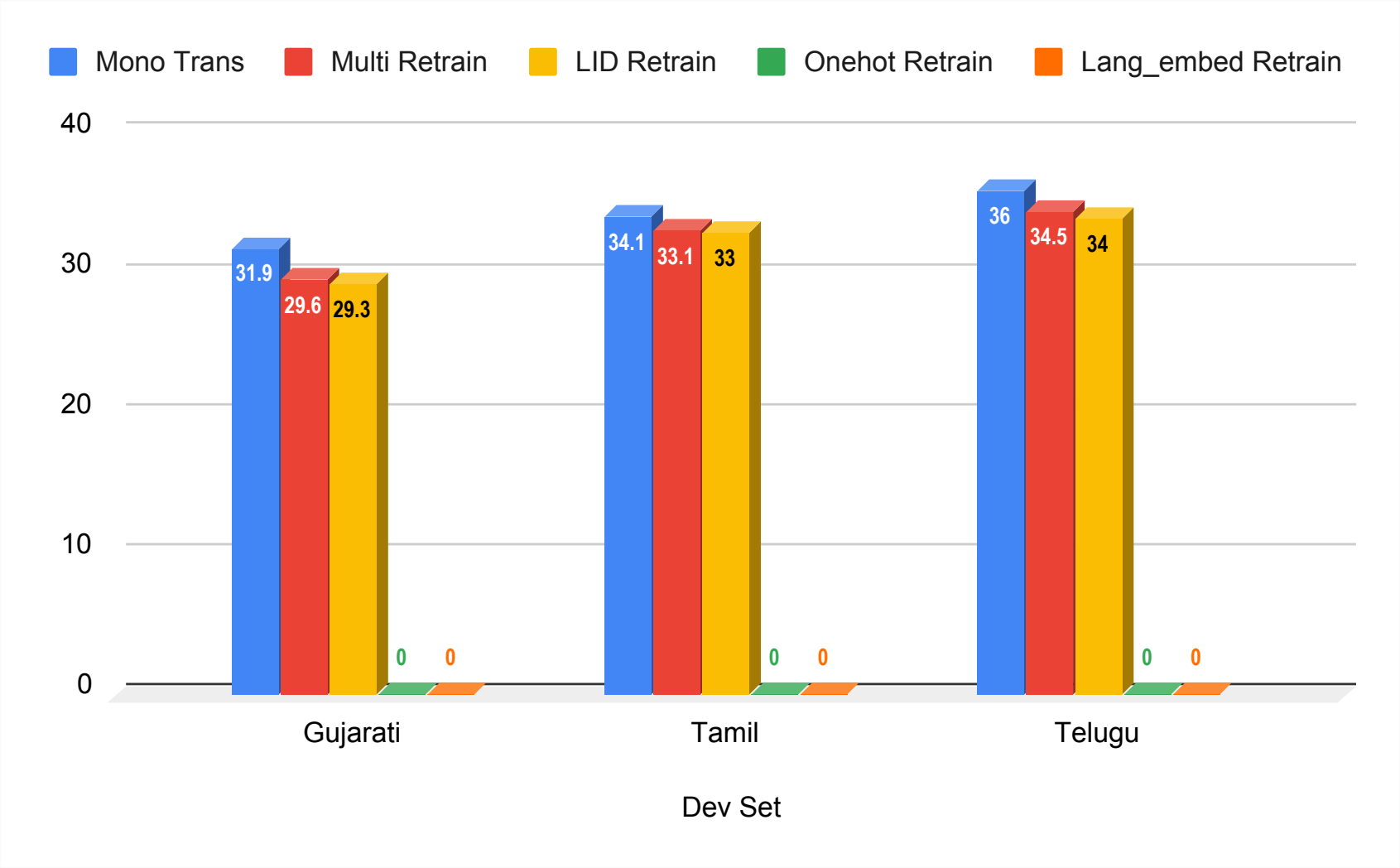

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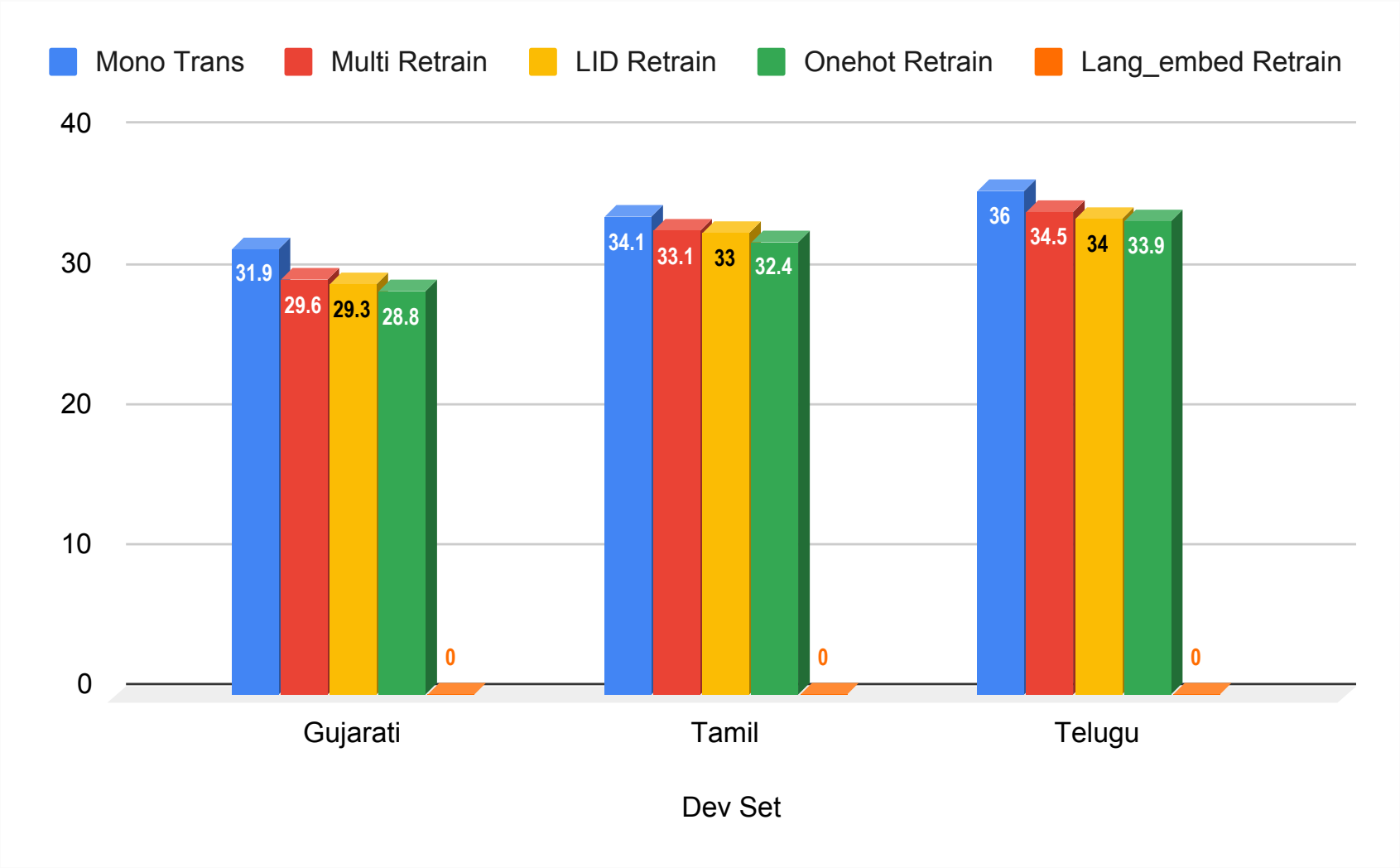

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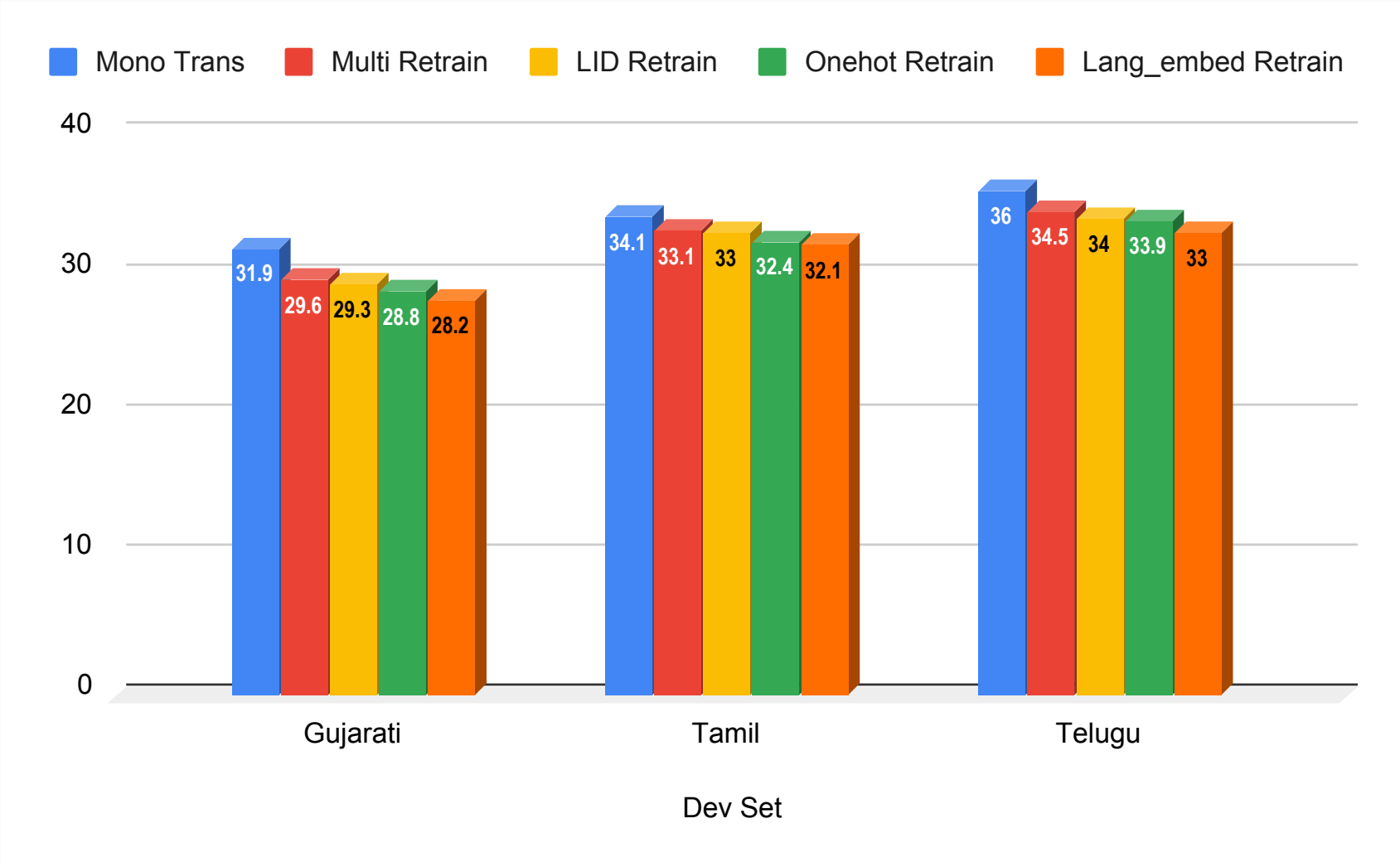

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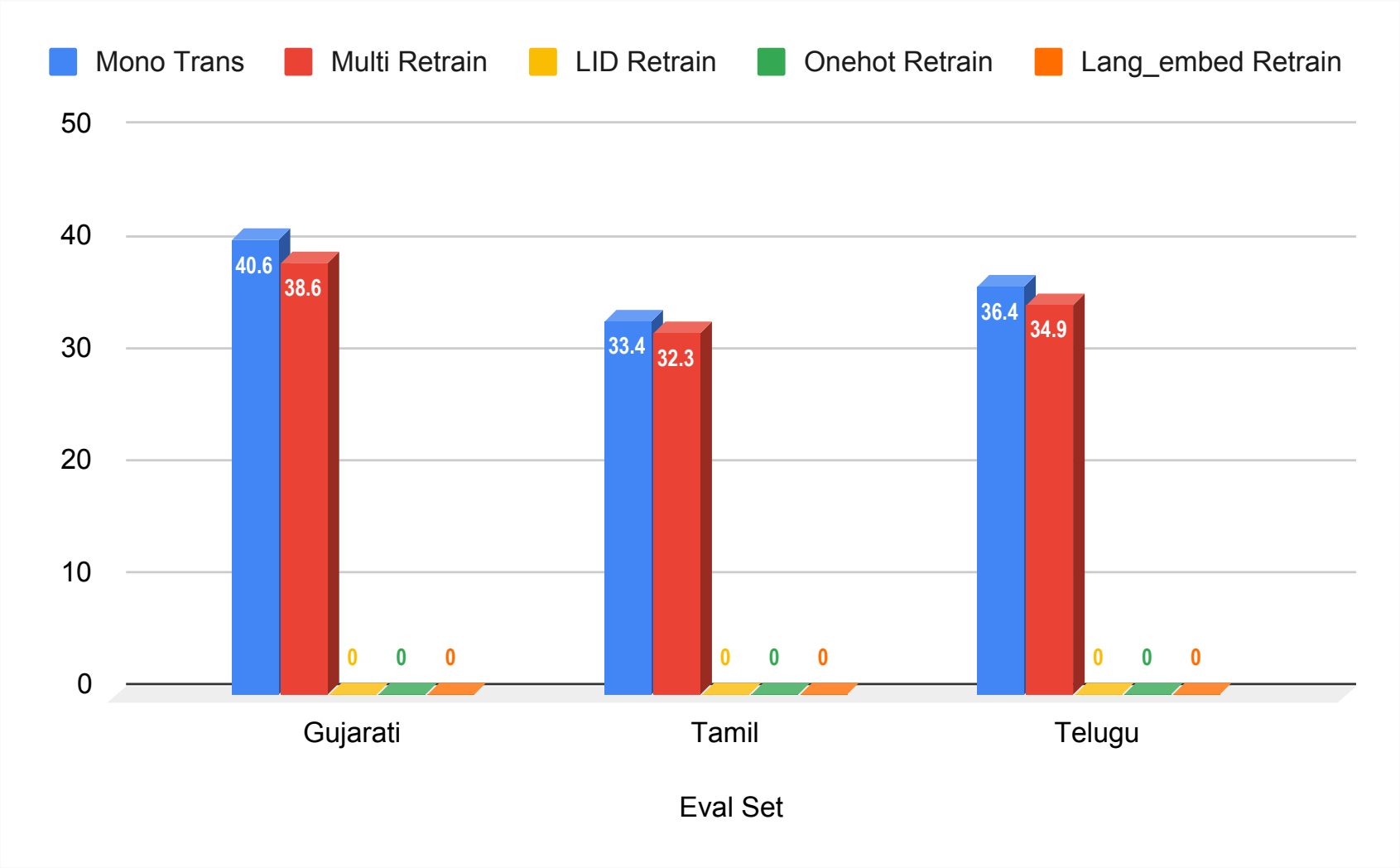

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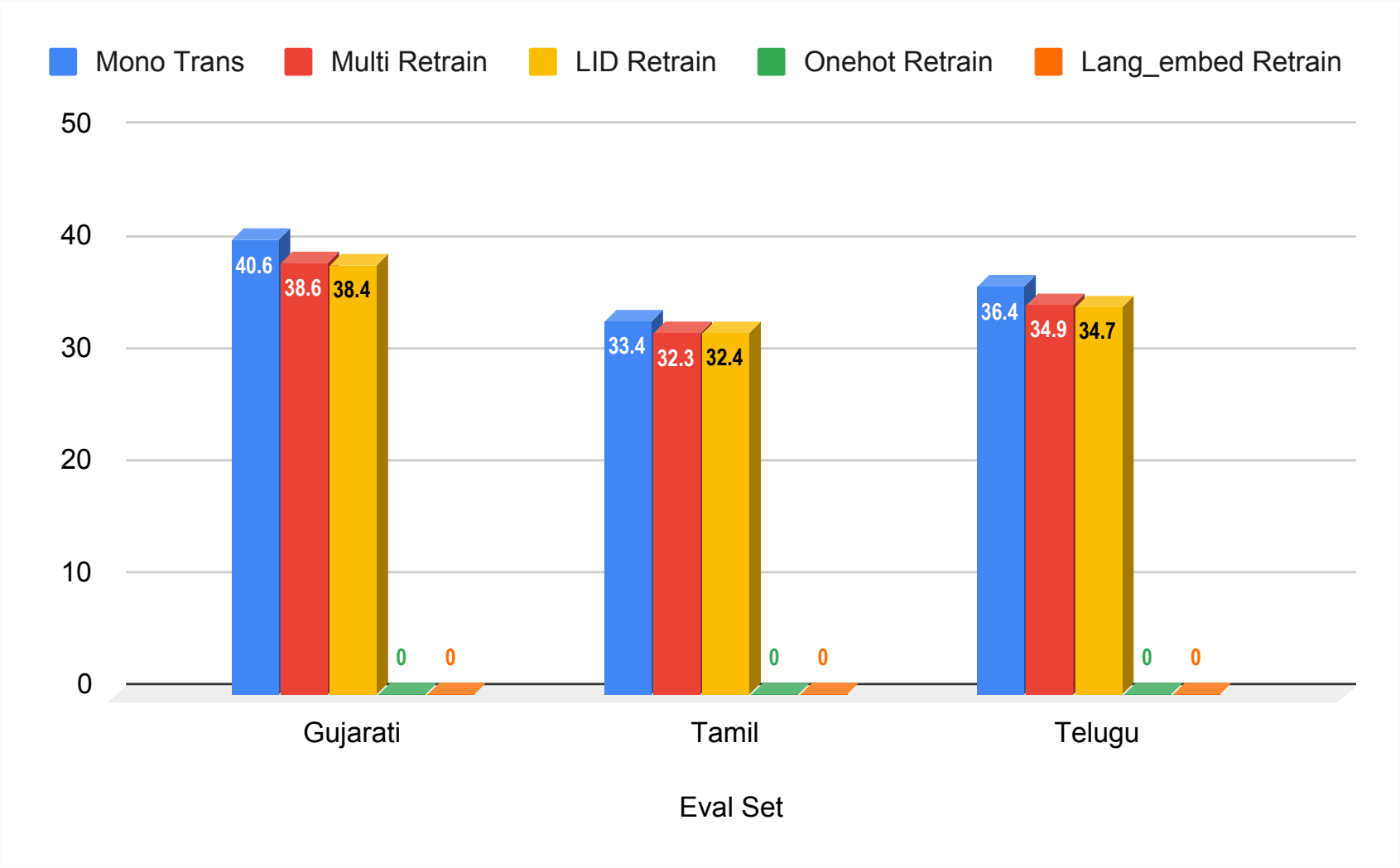

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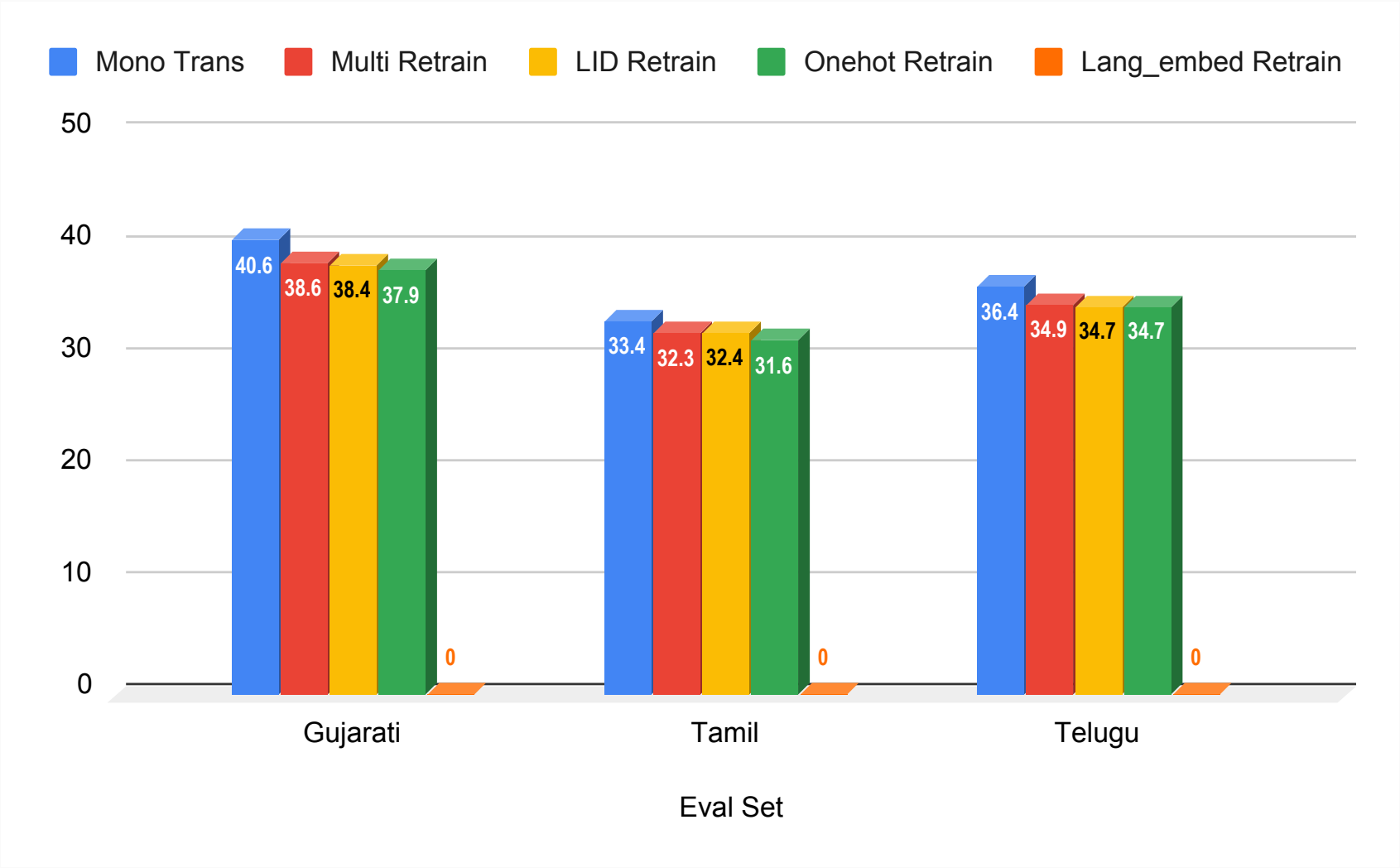

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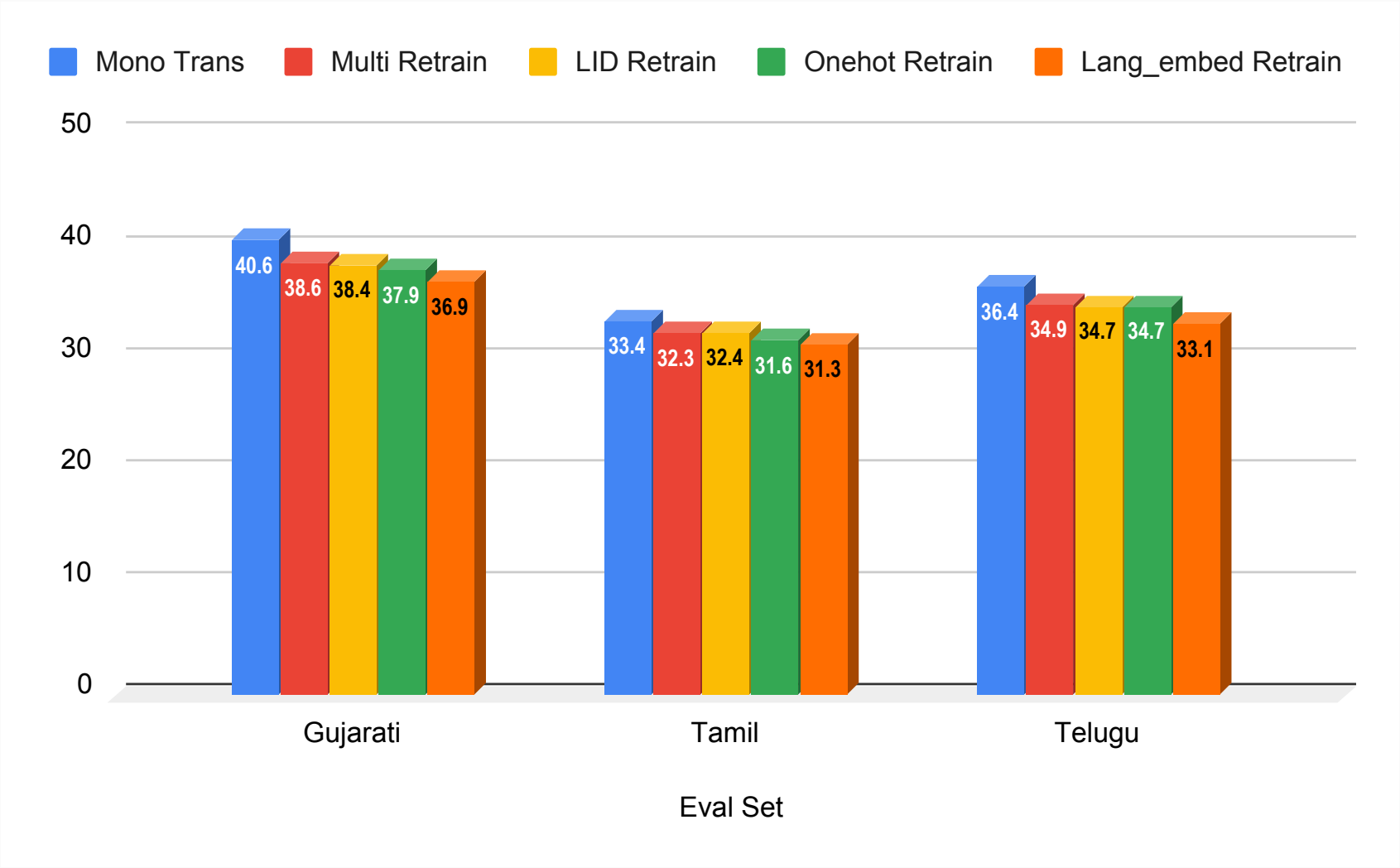

Conclusion

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- Making use of Language information while training/decoding improves model performance.
- Explored two ways of incorporating Language information
- Providing Language information at the Encoder by learning feature embeddings, gave the best performance.
- Fine tuning further improved the model performance.