Multilingual Coreference Resolution in Low-resource South Asian Languages

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Abstract

Coreference resolution involves the task of identifying text spans within a discourse that pertain to the same real-world entity. While this task has been extensively explored in the English language, there has been a notable scarcity of publicly accessible resources and models for coreference resolution in South Asian languages. We introduce a Translated dataset for Multilingual Coreference Resolution (TransMuCoRes) in 31 South Asian languages using off-the-shelf tools for translation and word-alignment. Nearly all of the predicted translations successfully pass a sanity check, and 75% of English references align with their predicted translations. Using multilingual encoders, two off-the-shelf coreference resolution models were trained on a concatenation of TransMuCoRes and a Hindi coreference resolution dataset with manual annotations. The best performing model achieved a score of 64 and 68 for LEA F1 and CoNLL F1, respectively, on our test-split of Hindi golden set. This study is the first to evaluate an end-to-end coreference resolution model on a Hindi golden set. Furthermore, this work underscores the limitations of current coreference evaluation metrics when applied to datasets with split antecedents, advocating for the development of more suitable evaluation metrics.

Keywords: Anaphora, Coreference, Multilingual, Translation, Alignment, OntoNotes, LitBank

1. Introduction

The phenomenon of referring to an expression previously mentioned in a discourse is widespread in natural languages. In the written text, it circumvents the repetition of expressions and engenders a sequence of coherent and interconnected sentences. For instance, consider the paragraph: "***John** is a good student. **He** asks intelligent questions and helps others. No wonder everybody loves **the boy**.*" These sentences are interconnected, as various referring expressions (highlighted in bold) are used to refer to the same entity named "*John*". Coreference resolution is an automated process that identifies referring expressions in a given text and locates the closest expression to which it refers. It acts as a useful preprocessing step and helps in many downstream tasks like entity linking (Kundu et al., 2018), Question-Answering (QA) (Bhattacharjee et al., 2020), and chatbots (Zhu et al., 2018).

Several end-to-end coreference resolution tools are currently available for English (Dobrovolskii, 2021), Arabic (Aloraini et al., 2020), and various European languages (David, 2022). However, to the best of our knowledge, no such tool is available for coreference resolution in any South Asian language, despite the presence of multiple works in this field (Sikdar et al., 2016; Senapati and Garain, 2013; Khandale and Mahender, 2019a; Ram and Devi, 2017). Our study is specifically focused on South Asian languages as they are native to

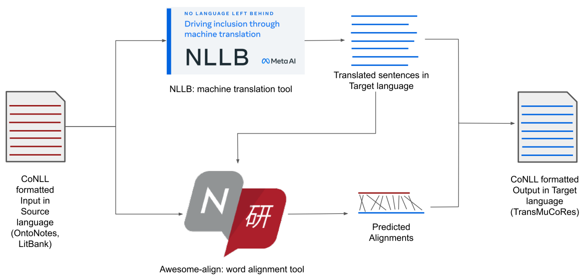

Figure 1: Overall pipeline used to construct the **Trans**lated dataset for **Mu**ltilingual **Co**reference **Res**olution (TransMuCoRes).

approximately 25% of the global population, and three of the ten most widely spoken languages worldwide hail from this region (Ethnologue, 2021). Consequently, the main contributions of our work are as follows:

1. We introduce[1] a **Trans**lated dataset for **Mu**ltilingual **Co**reference **Res**olution (TransMuCoRes)[2] in 31 South Asian languages.
2. We release checkpoints for two off-the-shelf coreference resolution models that have been fine-tuned on TransMuCoRes dataset and the manually annotated Hindi coreference resolution dataset by Mujadia et al. (2016).
3. We also highlight the limitations in current

[1]https://github.com/ritwikmishra/transmucores
[2]pronounced *trans-mew-cores*

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Language	Assamese	Awadhi	Bengali	Bhojpuri	Tibetan
Script	Bangla	Devanagri	Bangla	Devanagari	Uchen
FLORES-200 code	asm_Beng	awa_Deva	ben_Beng	bho_Deva	bod_Tibt
Language	Dzongkha	Gujarati	Hindi	Chhattisgarhi	Kannada
Script	Uchen	Gujarati	Devanagri	Devanagri	Kannada
FLORES-200 code	dzo_Tibt	guj_Gujr	hin_Deva	hne_Deva	kan_Knda
Language	Kashmiri	Magihi	Maithili	Malayalam	Marathi
Script	Arabic	Devanagari	Devanagri	Malayalam	Devanagri
FLORES-200 code	kas_Arab	mag_Deva	mai_Deva	mal_Mlym	mar_Deva
Language	Meitei	Burmese	Nepali	Odia	Punjabi
Script	Bangla	Burmese	Devanagri	Kalinga	Gurumukhi
FLORES-200 code	mni_Beng	mya_Mymr	npi_Deva	ory_Orya	pan_Guru
Language	Pashto	Persian	Santali	Sinhala	Sindhi
Script	Arabic	Arabic	Ol Chiki	Sinhala	Arabic
FLORES-200 code	pbt_Arab	prs_Arab	sat_Beng	sin_Sinh	snd_Arab
Language	Tamil	Telugu	Tajik	Uyghur	Urdu
Script	Tamil	Telugu	Cyrillic	Arabic	Arabic
FLORES-200 code	tam_Taml	tel_Telu	tgk_Cyrl	uig_Arab	urd_Arab
Language	Uzbek				
Script	Latin				
FLORES-200 code	uzn_Latn				

Table 1: A catalogue of South Asian languages supported by TransMuCoRes. Note: some Central Asian languages (Uzbek/Tajik) have native speakers in Afghanistan as well (Mobashir, 2021).

evaluation metrics while evaluating the resolved coreferences having split antecedants.

2. Related Work

Early works in coreference resolution used constituency trees in Hobbs algorithm (Hobbs, 1978), semantic features (Lappin and Leass, 1994), and syntactic features (Haghighi and Klein, 2009). A mention-ranking architecture of coreference resolution using pretrained word embeddings and neural networks was first proposed by Lee et al. (2017). Each mention is denoted by a span of words (tokens) in the text. Equation 1 is used to calculate a score for a given pair of spans. A dummy antecedent is denoted by the symbol ϵ, and the value of $S(i, j = \epsilon)$ is always taken as zero. The score (S) represents the strength of coreference link between the span *i* and *j*. In equation 1, the mention score (s_m) and antecedent score (s_a) are calculated using the span representations which are obtained with the help of pretrained word embeddings and Bi-LSTM neural network.

$$S(i, j) = s_m(i) + s_m(j) + s_a(i, j) \quad (1)$$

The aim of the model was to learn a conditional probability distribution mentioned in equation 2 where $Y(i)$ represents the set of all the possible mention spans before the span *i* during the discourse.

$$P(y_i) = \frac{e^{S(i,y_i)}}{\sum_{y' \in Y(i)} e^{S(i,y')}} \quad (2)$$

The approach introduced by Lee et al. (2017) has served as a source of inspiration for various studies in the realm of end-to-end coreference resolution. Joshi et al. (2019) observed notable performance improvements when applying a pretrained transformer-based model by Devlin et al. (2019), rather than static word embeddings, for text encoding. Additionally, Joshi et al. (2020) employed a span-based objective to pretrain a transformer-based model, which they used for text encoding and coreference resolution, following the approach by Lee et al. (2017). Meanwhile, Xu and Choi (2020) empirically demonstrated that the Higher-Order Inference (HOI) method proposed by Lee et al. (2018) often has minimal, and at times, even negative, impact on coreference resolution.

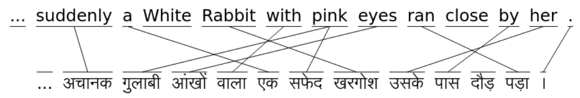
In terms of South Asian languages, several early works have explored Hindi coreference resolution, including the work by Dutta et al. (2008), which proposed a modified Hobbs algorithm. Many works have used hand-crafted rules to resolve coreferences in Hindi (Dakwale et al., 2013; Lata et al., 2023), Marathi (Khandale and Mahender, 2019b), and Telugu (Jonnalagadda and Mamidi, 2015). Some works have used Person-Number-Gender (PNG) features to detect mentions and Conditional Random Field (CRF) model to predict coreferential links in Tamil (Akilandeswari and Devi, 2012; Ram and Devi, 2020) and Hindi (Devi et al., 2014). Incorporating PNG features for some South Asian language poses significant challenges due to their distinct inflectional system (Gandhe et al., 2011). Unlike European languages, many South Asian languages inflect verbs according to the actions of the sentence rather than the agents (Shapiro, 2003; Singh and Sarma, 2011). Furthermore, inflectional errors are prevalent in such languages (Sonawane et al., 2020). Therefore, in order to advance multilingual coreference resolution, neural techniques for automated feature extraction are essential. Singh et al. (2020) resolved anaphoras in Hindi using Gated Recurrent Unit (GRU) with static word embeddings. However, no public tool or source code is available for any of the aforementioned works in South Asian languages.

3. Dataset

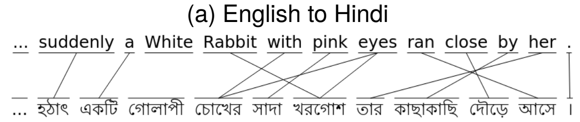
In this research, we incorporated the following manually annotated English coreference resolution datasets: (i) OntoNotes, widely recognized as a benchmark dataset for coreference resolution (Weischedel et al., 2013; Shridhar et al., 2023; Xia and Van Durme, 2021), and (ii) LitBank, which contains longer documents and includes singleton mentions, i.e., mentions that occur only once in the discourse (Recasens et al., 2013; Bamman et al., 2020). It is worth noting that OntoNotes lacks sin-

		#sents	#mentions	#coreference clusters	#split-antecedants	#singletons	#docs
TransMuCoRes	Train	1839883	3821540	1135906	93668	350017	87946
	Development	224911	472083	148189	10505	46399	10890
	Test	255466	558093	165664	12944	59279	11294
Mujadia et al., 2016	Train	2839	10512	3217	287	538	220
	Development	347	1306	387	31	58	27
	Test	347	1255	399	36	79	28

Table 2: Data statistics for TransMuCoRes across 31 South Asian languages, and data statistics of the Mujadia et al. (2016) dataset in Hindi. It can be observed that the ratio of #split-antecedent with #mentions is similar in both the datasets, with percentages of 2.4% and 2.7% for TransMuCoRes and the Mujadia et al. (2016) dataset, respectively.



(a) English to Hindi



(b) English to Bengali

Figure 2: Visualizations of word-alignments predicted by the fine-tuned multilingual checkpoint by Dou and Neubig (2021) in high-recall setting. It can be observed that word-order of Hindi and Bengali is different than English.

	Mentions		
	Aligned	**Misaligned**	**Non-Aligned**
simalign with multi-lingual BERT (mbert)	53.7%	**6.1%**	40.1%
simalign with XLM-RoBERTa (xlmr)	58.5%	7.1%	34.3%
awesome-align without high recall	66.7%	9.4%	23.8%
awesome-align with high recall	**72.5%**	11.4%	**16.2%**

Table 3: Alignment statistics from awesome-align (Dou and Neubig, 2021) and simalign (Sabet et al., 2020) on TransMuCoRes shows that high-recall checkpoint of awesome-align method gives most number of aligned mentions.

gleton mentions, which led us to utilize the LitBank dataset in our study. Kübler and Zhekova (2011) and Yu et al. (2020) has demonstrated that detecting singleton mentions impacts the performance of a coreference resolution system.

Figure 1 provides an overview of the pipeline utilized for constructing individual samples within TransMuCoRes. We used *nllb-200-1.3B* model (Team et al., 2022) to translate the English sentences to its target language. Table 1 shows the languages supported by TransMuCoRes. We maintained a sanity-check for the generated translations, considering it a failure if the translation primarily consisted of repeated punctuation. The English sentences whose generated translations failed the sanity check were re-translated using the larger *facebook/nllb-200-3.3B* model. After this we observed that only 111 translations failed the sanity-check out of more than 3 million translations. Nearly 12% sanity-check failures were from Sindhi language. Appendix A contains the language-wise distribution of sanity-check in Table 7.

When translating an English sentence into South Asian languages, the position of mentions within the translated sentence can change due to the free word order characteristics of these languages (Dayal and Mahajan, 2004). To illustrate this, consider an excerpt from a sentence in LitBank: "... suddenly a White Rabbit with pink eyes ran close by her." This sentence is translated into Hindi (... अचानक गुलाबी आंखों वाला एक सफेद खरगोश उसके पास दौड़ पड़ा ।) and Bengali (... হঠাৎ একটি গোলাপী চোখের সাদা খরগোশ তার কাছাকাছি দৌড়ে আসে ।) using the NLLB model. Figure 2 provides a visual representation of the free-word nature of Hindi and Bengali in these translations[3].

In order to generate word-level alignments after the translation step, we used the high-recall multilingual checkpoint from the awesome-align tool (Dou and Neubig, 2021). An aligned mention refers to a continuous span of words in the target language that corresponds to a mention in the source (English) language. If a mention is aligned to a non-continuous span of words in the target language, it is termed a misaligned mention. In cases where a mention lacks alignment with any word in the target language, it is categorized as a non-aligned mention. Misaligned and non-aligned mentions are not marked as mentions in our work. We observed that it gave more aligned mentions as compared to Sabet et al. (2020). Table 3 shows a comparison of the two methods. Figure 2 con-

[3]Visualizations created by `https://vilda.net/s/slowalign/`

English	... suddenly [a White Rabbit with pink eyes]$_4$ ran close by [her]$_1$.	**mni_Beng**	... নোংমদা মচুগী মমি লৈবা ৱাইত ৰেবিন অমনা মহাক্কী মনাক্তা চংলকখি ।
asm_Beng	... হঠাতে এটা [ৰঙা চকু থকা বগা কণী]$_4$ তাইৰ ওচৰলৈ দৌৰি আহিল ।	**mya_Mymr**	... [□ရုတ်တရက် ပန်းရောင်မျက်လုံးတွေနဲ့ ယုန်ဖြူတစ်ကောင်□]$_4$ သူမနားကို ပြေးလာပါတယ်။
awa_Deva	... एकाएक उ एक सफेद खरगोश स भरा गुलाबी आँखी क ओकरे लगे [दौड़िके]$_1$ आवा ।	**npi_Deva**	... अचानक गुलाबी आँखा भएको सेतो खरगोश [उनको]$_1$ नजिकै दौड्यो ।
ben_Beng	... হঠাৎ একটি গোলাপী চোখের সাদা খরগোশ [তার]$_1$ কাছাকাছি দৌড়ে আসে ।	**ory_Orya**	... [ହଠାତ୍ ଏକ ଗୋଲାପୀ ଆଖିର]$_4$ ହ୍ୱାଇଟ୍ ରାବିଟ୍ ତାଙ୍କ ପାଖରେ ଦୌଡ଼ି ଆସିଲା ।
bho_Deva	... अचानक उहो [गुलाबी आँखिन क एक सफेद]$_4$ खरगोश ओकरे लगे दौड़त आवा ।	**pan_Guru**	... ਅਚਾਨਕ [ਇੱਕ ਗੁਲਾਬੀ ਅੱਖਾਂ ਵਾਲਾ ਵ੍ਹਾਈਟ ਰੈਬਿਟ]$_4$ [ਉਸਦੇ]$_1$ ਨੇੜੇ ਭੱਜਿਆ .
bod_Tibt	... [ག་མོ་ལ་མིག་དམར་དམར་པོ་ཡོད་པའི་རྣ་ཅོ་དཀར་པོ་ཞིག་ཉེ་བར་རྒྱུག་ཡོང་གི་རེད།]$_4$	**pbt_Arab**	خرگوش سپین یو ناخاپه چې کله ... ورغله نږدې سره سترګو ګلابي د
dzo_Tibt	...མོ་རང་ལུ་ (མོ་ལུ་ཚ་གྲང་ཡོདཔ་ལས་ མོ་རང་ལུ) (མོ་ལུ་ཚ་གྲང་ཡོདཔ་ལས་) མོ་རང་ལུ་ (མོ་ལུ་) མོ་རང་ལུ་)	**prs_Arab**	با سفید خرگوش □یک ناگهان که وقتی ... دوید [□او□]$_1$ نزدیک به صورتی های [چشم□]$_4$
guj_Gujr	... અચાનક [એક ગુલાબી આંખોવાળો]$_4$ સફેદ સસલું [તેની]$_1$ નજીક દોડ્યો.	**sat_Beng**	...[illegible] ।
hin_Deva	... अचानक [गुलाबी आंखों वाला एक सफेद खरगोश]$_4$ [उसके]$_1$ पास दौड़ पड़ा ।	**sin_Sinh**	... රෝස [පැහැති ඇස් ඇති]$_4$ සුදු රැබිණක් ඇය අසල දිව ආ විට .
hne_Deva	... अचानक गुलाबी आंखी वाला [एक सफेद खरगोश]$_4$ ओखर करा दौड़त आईस ।	**snd_Arab**	گلابي ڪنبيءَ اچو هڪ اوچتو جڏهن ... ڊوڙيو ويجهو جي هن سان اکين
kan_Knda	... ಇದ್ದಕ್ಕಿದ್ದಂತೆ [ಗುಲಾಬಿ ಕಣ್ಣಿನ ಬಿಳಿ ಮೊಲವು]$_4$ [ಅವಳ]$_1$ ಹತ್ತಿರ ಓಡಿತು .	**tam_Taml**	... ஒரு வெள்ளை முயல் ரோஜா கண்களுடன் [அவளிடம்]$_1$ நெருங்கி ஓடியது .
kas_Arab	خرگوش سفید اکھ اچانک [رلان-] ... نزدیک تیلہٕ اوس ستی چشمن گلابی ییمہٕ	**tel_Telu**	... [ఒక బ్లూ-కళ్ళు గల]$_4$ వైట్ కనేబిట్ [ఆమె]$_1$ దగ్గరకు వచ్చింది .
mag_Deva	... अचानक एगो गुलाबी [आँख वाला सफेद खरगोश]$_4$ ओकरा नगीच दौड़लइ ।	**tgk_Cyrl**	... ки ногаҳон [як харгӯши сафед бо чашмони гулобӣ]$_4$ ба наздикии [ӯ]$_1$ давида омад .
mai_Deva	... अचानक [एकटा गुलाबी-आँखि]$_4$ वला गोरगो ओकर लगमे दौड़ि [गेल]$_1$ ।	**uig_Arab**	ئويلىنىپ ئۇ ، باقتىغۇ ئويلىنىپ ... باقتىغۇ ، ئۇ ئويلىنىپ ئۇ باقتىغۇ
mal_Mlym	... പെട്ടെന്ന് ഒരു റോസ് കണ്ണുകളുള്ള വൈറ്റ് ക്നീറ്റ് [അവളുടെ]$_1$ അടുത്ത് ഓടി .	**urd_Arab**	آنکھوں گلابی خرگوش سفید ایک اچانک جب ... گیا۔ بھاگ قریب کے [□اس□]$_1$ ساتھ کے
mar_Deva	... अचानक [एक गुलाबी डोळे असलेला पांढरा ससा]$_4$ [तिच्या]$_1$ जवळ धावला .	**uzn_Latn**	... [unga]$_1$ yaqinlashib ketayotgan qizg‘al ko‘zli Oq quyon ko‘zidan o‘tib qoldi .

Table 4: Coreference data after processing the translated sentences and aligned words. Coreference clusters for "*Rabbit*" and "*Alice*" are highlighted in green and pink color, respectively. The English sentence in this table is an excerpt from a sentence in LitBank (Bamman et al., 2020). Translation errors can be observed in dzo_Tibt where words are repeated. Alignment errors can be observed in ben_Beng where the mention "*a White Rabbit with pink eyes*" is misaligned despite perfect translation. Note: Arabic fonts are to be read left to right due to issues in the LaTeX typefonts.

tains Hindi and Bengali translations because we observed that most aligned mentions were seen in these languages. Appendix A contains the alignment statistics for each language in Table 8.

The proposed TransMuCoRes was constructed using the following three primary components: (i) manually annotated mentions and coreference clusters in the English dataset, (ii) predicted translations, and (iii) aligned mentions between English sentences and translated sentences. For each language, dummy values were assigned in the placeholder of constituency parse trees and speaker information. This was necessitated by the absence of publicly available tools for generating constituency parse trees for South Asian languages and the lack of speaker information in the Litbank and Mujadia et al. (2016) dataset.

Table 4 highlights errors in translation and alignment observed in the TransMuCoRes construction pipeline. Due to imperfect translations and alignments, we opted to train various off-the-shelf coreference resolution models with a manually annotated coreference resolution dataset as well. We utilized the Hindi coreference resolution dataset introduced by Mujadia et al. (2016), because it is the only publicly available manually annotated dataset for coreference resolution in a South Asian language (Hindi). For details on the statistics of TransMuCoRes and the dataset by Mujadia et al. (2016), please refer to Table 2. While we retained the train:dev:test splits for OntoNotes, we had to establish similar splits for LitBank and the dataset by Mujadia et al. (2016). The splits will be released as part of the resources to encourage a standardized evaluation of future models.

4. Coreference Resolution Models

In this study, we used the following off-the-shelf coreference resolution models: (i) wl-coref (Dobrovolskii, 2021), and (ii) fast-coref (Toshniwal et al., 2021). We selected these models primarily because they offer fine-tuning scripts for a new CoNLL formatted data. Moreover, wl-coref and fast-coref delivers performances only 3-4% lower than the state-of-the-art model on the OntoNotes benchmark[4]. Unfortunately, we encountered challenges in finding comparable training scripts for state-of-the-art coreference resolution models on the OntoNotes dataset (Liu et al., 2022; Bohnet et al., 2023; Werlen and Henderson, 2022). Due to limitations in available resources, fine-tuning of the LingMess model (Otmazgin et al., 2023) was not pursued in this study. Similarly, other coreference models (Otmazgin et al., 2022; Kirstain et al., 2021), which have not demonstrated superior performance compared to wl-coref and fast-coref on OntoNotes benchmark, were also not subjected to fine-tuning in our investigation. Furthermore, coreference models such as those proposed by Aloraini et al. (2020) and Yu et al. (2020) relied on features extracted from pretrained word embeddings specific to individual languages, rendering the process of fine-tuning for multilingual data less straightforward. To adapt wl-coref and fast-coref for multilingual data, we harnessed the capabilities of multilingual BERT (mbert) by Devlin et al. (2019) and base XLM-RoBERTa (xlmr) by Conneau et al. (2020) as text encoders. This approach allowed for the fine-tuning of a single model with multilingual data.

The fast-coref model is constructed through the utilization of the Longformer encoder (Beltagy et al., 2020) within the longdoc coreference resolution framework (Toshniwal et al., 2020). It was noted that concurrent training employing data augmentation methodologies such as pseudo-singletons enhanced the model's performance across various datasets spanning diverse domains.

[4] https://paperswithcode.com/sota/coreference-resolution-on-ontonotes

The wl-coref model relies on a head-finding mechanism via dependency parse trees, which compelled us to fine-tune the model exclusively for languages with publicly available dependency parsers. Therefore, we fine-tuned wl-coref model on Hindi, Tamil, Telugu, Urdu, and Marathi data using the dependency parser of Stanza (Qi et al., 2020) library. The fine-tuned wl-coref model was evaluated in zero-shot manner for the remaining languages.

It is worth noting that the Stanza dependency parsing tool frequently generates parse trees by subdividing words into subword components. For instance, in the tokenization of the sentence, கடுமையான வலிகளும் , திடீர் தலைச்சுற்றலும் , பின்னர் துளைகளிலிருந்து இரத்தப்போக்குக , மற்றும் உடைப்புகளும் இருந்தன . *(There were severe pains, sudden dizziness, then bleeding from the pores, and ruptures.)*, the word கடுமையான *(severe)* is broken into கடுமைய் *(severely)* and ஆன *(became)*. It becomes evident that a mere concatenation of subwords does not yield an equivalent representation to the original token. It is important to underline that the TransMuCoRes dataset exclusively provides word-level annotations. Therefore, obtaining a dependency parse tree at the word level, rather than at the subword level, holds significant relevance. To address this challenge, we harnessed the utility of the awesome-align word alignment tool to establish a mapping between subwords and their corresponding original words.

4.1. Evaluation Metrics

In this study, we employ evaluation metrics traditionally utilized for coreference resolution (Joshi et al., 2020; Toshniwal et al., 2021; Paun et al., 2022). MUC functions as a link-based metric, where a lower MUC value indicating a substantial need for links to be added or deleted in the predicted coreference chains to align them closely with the ground-truth coreference chain. Conversely, B^3 is a mention-based metric that assesses how effectively the coreference model groups together corefering mentions while keeping non-corefering mentions distinct. CEAFe reflects the degree of overlap between aligned key-response pairs, with a higher value indicating greater alignment between key and response. The CoNLL metric is derived from an unweighted average of MUC, B^3, and CEAFe. Furthermore, LEA is a link and entity-based metric, with a higher LEA value indicating accurate resolution of long coreference chains. These metrics have been elaborated in more detail by (Moosavi and Strube, 2016).

				Mentions			MUC			B^3			CEAFe			LEA			CoNLL
				P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	F1
wl-coref (Dobrovolskii, 2021)	5 langs	mbert	dev	62	**77**	69	57	**67**	61	42	**55**	47	37	55	44	36	49	42	51
			test	64	**79**	71	61	70	65	42	**56**	48	34	53	41	37	**51**	43	52
		xlmr	dev	**67**	**77**	**72**	**63**	**67**	**65**	**49**	**55**	**52**	**41**	**59**	**48**	**43**	**50**	**46**	**55**
			test	**68**	**79**	**73**	**66**	**71**	**69**	**49**	**56**	**52**	**37**	**58**	**45**	**44**	**51**	**48**	**55**
	All langs	mbert	dev	37	68	48	32	56	41	22	**46**	30	20	45	28	18	**40**	25	33
			test	39	70	50	34	59	44	22	**47**	30	19	43	26	18	**42**	26	33
		xlmr	dev	45	62	52	40	51	45	29	41	34	**25**	45	**32**	25	36	29	37
			test	46	63	53	42	54	47	29	41	34	**23**	44	**30**	25	37	30	37
fast-coref (Toshniwal et al., 2021)	All langs	mbert	dev	44	**76**	56	41	59	48	28	42	34	18	55	27	24	36	29	36
			test	46	76	58	44	62	52	29	42	34	17	53	26	25	37	30	37
		xlmr	dev	**48**	**76**	**59**	**46**	**61**	**52**	**33**	44	**38**	21	**59**	31	**29**	39	**33**	**41**
			test	**50**	**77**	**60**	**49**	**64**	**56**	**34**	44	**38**	20	**58**	29	**30**	40	**34**	**41**

Table 5: Performance of fine-tuned fast-coref (Toshniwal et al., 2021) with xlmr encoder is better than zero-shot performance of wl-coref (Dobrovolskii, 2021) on all the languages. However, wl-coref is found to be performing well for the 5 languages on which it is fine-tuned.

Language	fast-coref (Toshniwal et al., 2021) vs wl-coref (Dobrovolskii, 2021) on fine-tuned xlmr													
	Split	Mentions F1	MUC F1	B^3 F1	CEAFe F1	LEA F1	CoNLL F1	Split	Mentions F1	MUC F1	B^3 F1	CEAFe F1	LEA F1	CoNLL F1
asm_Beng	DEVLOPMENT	45 vs 46	38 vs 35	25 vs 24	22 vs 26	20 vs 18	28 vs 28	TEST	47 vs 46	41 vs 37	25 vs 23	21 vs 24	20 vs 18	29 vs 28
awa_Deva		50 vs 42	41 vs 32	29 vs 25	27 vs 28	23 vs 19	33 vs 28		51 vs 43	45 vs 33	28 vs 23	25 vs 26	23 vs 18	33 vs 27
ben_Beng		74 vs 73	67 vs 66	51 vs 52	45 vs 48	46 vs 47	55 vs 55		76 vs 75	71 vs 70	52 vs 53	43 vs 46	48 vs 49	56 vs 56
bho_Deva		52 vs 41	46 vs 33	31 vs 24	27 vs 26	26 vs 19	35 vs 27		54 vs 43	49 vs 35	31 vs 24	25 vs 24	26 vs 19	35 vs 28
bod_Tibt		63 vs 6	44 vs 3	17 vs 2	10 vs 3	12 vs 2	24 vs 3		64 vs 6	48 vs 3	18 vs 3	10 vs 4	14 vs 2	25 vs 3
dzo_Tibt		18 vs 4	15 vs 3	9 vs 2	5 vs 2	6 vs 1	10 vs 2		19 vs 5	16 vs 4	10 vs 2	6 vs 3	7 vs 2	10 vs 3
guj_Gujr		74 vs 73	66 vs 65	50 vs 51	45 vs 48	45 vs 46	54 vs 55		75 vs 74	69 vs 68	50 vs 51	42 vs 45	45 vs 47	54 vs 55
hin_Deva		75 vs 74	68 vs 68	52 vs 54	46 vs 50	47 vs 49	55 vs 58		76 vs 76	71 vs 72	52 vs 55	43 vs 48	48 vs 51	55 vs 58
hne_Deva		48 vs 39	41 vs 29	28 vs 21	27 vs 24	23 vs 16	32 vs 25		48 vs 40	43 vs 31	28 vs 21	25 vs 22	23 vs 16	32 vs 25
kan_Knda		73 vs 71	65 vs 63	50 vs 50	45 vs 48	44 vs 45	53 vs 54		74 vs 73	68 vs 67	50 vs 51	42 vs 46	46 vs 46	53 vs 55
kas_Arab		33 vs 13	27 vs 8	17 vs 7	16 vs 10	13 vs 5	20 vs 8		34 vs 14	30 vs 9	17 vs 6	15 vs 9	13 vs 4	20 vs 8
mag_Deva		54 vs 47	47 vs 38	32 vs 28	28 vs 28	27 vs 22	36 vs 31		56 vs 50	51 vs 41	32 vs 27	26 vs 27	28 vs 22	36 vs 32
mai_Deva		48 vs 38	42 vs 32	28 vs 22	25 vs 22	24 vs 18	32 vs 25		50 vs 39	45 vs 34	29 vs 22	23 vs 21	25 vs 18	32 vs 25
mal_Mlym		66 vs 65	58 vs 56	43 vs 44	38 vs 44	37 vs 37	46 vs 48		68 vs 67	62 vs 60	44 vs 45	36 vs 42	39 vs 39	47 vs 49
mar_Deva		72 vs 71	65 vs 64	49 vs 51	44 vs 47	44 vs 46	52 vs 54		74 vs 72	68 vs 68	50 vs 52	40 vs 44	45 vs 47	53 vs 54
mni_Beng		30 vs 9	24 vs 4	14 vs 3	11 vs 5	9 vs 1	16 vs 4		33 vs 10	27 vs 6	14 vs 3	10 vs 5	10 vs 1	17 vs 4
mya_Mymr		61 vs 53	52 vs 42	37 vs 32	34 vs 35	31 vs 26	41 vs 36		63 vs 54	55 vs 46	36 vs 32	31 vs 33	31 vs 26	41 vs 37
npi_Deva		74 vs 73	68 vs 66	52 vs 53	46 vs 49	47 vs 47	55 vs 56		76 vs 75	71 vs 70	53 vs 54	44 vs 47	49 vs 49	56 vs 57
ory_Orya		22 vs 22	19 vs 13	10 vs 9	8 vs 12	7 vs 4	12 vs 11		24 vs 23	22 vs 15	10 vs 8	8 vs 12	7 vs 4	13 vs 12
pan_Guru		71 vs 70	64 vs 63	48 vs 49	43 vs 47	43 vs 44	51 vs 53		73 vs 72	68 vs 67	48 vs 50	40 vs 44	44 vs 45	52 vs 53
pbt_Arab		33 vs 29	31 vs 21	18 vs 14	15 vs 17	15 vs 9	21 vs 17		36 vs 31	34 vs 23	19 vs 13	14 vs 17	16 vs 9	22 vs 18
prs_Arab		69 vs 64	63 vs 56	47 vs 43	40 vs 42	42 vs 37	50 vs 47		70 vs 66	66 vs 60	46 vs 44	37 vs 39	42 vs 39	50 vs 48
sat_Beng		11 vs 4	10 vs 2	5 vs 2	3 vs 2	4 vs 1	6 vs 2		13 vs 5	12 vs 4	6 vs 2	3 vs 2	4 vs 1	7 vs 3
sin_Sinh		22 vs 22	18 vs 13	10 vs 9	8 vs 13	7 vs 5	12 vs 11		24 vs 23	22 vs 15	11 vs 9	8 vs 12	8 vs 5	14 vs 12
snd_Arab		30 vs 31	26 vs 22	15 vs 14	13 vs 18	12 vs 9	18 vs 18		31 vs 32	28 vs 24	15 vs 14	12 vs 18	12 vs 10	18 vs 18
tam_Taml		71 vs 70	63 vs 63	47 vs 50	43 vs 49	42 vs 44	51 vs 54		72 vs 72	66 vs 66	48 vs 50	40 vs 45	43 vs 45	51 vs 54
tel_Telu		71 vs 71	64 vs 64	48 vs 51	43 vs 48	43 vs 46	52 vs 54		73 vs 73	68 vs 68	50 vs 52	39 vs 45	45 vs 48	52 vs 55
tgk_Cyrl		61 vs 16	52 vs 11	37 vs 8	33 vs 11	31 vs 6	41 vs 10		62 vs 15	55 vs 11	37 vs 7	30 vs 10	32 vs 5	41 vs 10
uig_Arab		21 vs 25	15 vs 13	9 vs 10	9 vs 15	6 vs 5	11 vs 13		21 vs 26	17 vs 16	8 vs 10	8 vs 14	6 vs 6	11 vs 13
urd_Arab		70 vs 71	63 vs 64	47 vs 50	41 vs 47	42 vs 45	51 vs 54		72 vs 72	67 vs 67	47 vs 50	39 vs 44	43 vs 45	51 vs 54
uzn_Latn		63 vs 60	54 vs 50	40 vs 39	38 vs 40	34 vs 33	44 vs 43		64 vs 60	57 vs 53	39 vs 38	35 vs 37	34 vs 33	43 vs 43
Mujadia et al. (2016)		50 vs 78	45 vs 74	35 vs 66	33 vs 62	31 vs 62	38 vs 67		54 vs 79	51 vs 76	38 vs 68	31 vs 60	34 vs 64	40 vs 68
Overall		59 vs 52	52 vs 45	38 vs 34	31 vs 32	33 vs 29	41 vs 37		60 vs 53	56 vs 47	38 vs 34	29 vs 30	34 vs 30	41 vs 37

Table 6: The wl-coref (Dobrovolskii, 2021) method performs better than fast-coref (Toshniwal et al., 2021) for the languages on which it was fine-tuned (Hindi, Tamil, Telugu, Urdu, and Marathi).

5. Results

In this study, we utilized evaluation scripts developed by Paun et al. (2022). Table 5 illustrates the strong performance of the wl-coref method when evaluating languages it was fine-tuned on. This is confirmed from the findings in Table 6 that wl-coref performs better than fast-coref only on those languages on which it was fine-tuned. Notably, wl-coref achieves the highest performance on our test split of the golden set, with scores of 68 for LEA F1 and 64 for CoNLL F1. Our work is the first to release coreference resolution tools for Hindi and report their performance on the golden set by Mujadia et al. (2016). We also observed that the performance of both the models improves when singletons are ignored during the evaluation. Table 10 and Table 11 in Appendix A illustrates the same. In order to reconstruct the proposed TransMuCoRes, 14 GB of GPU memory is required, and the process may extend up to three months in duration on a single GPU. Similarly, the fine-tuning of coreference resolution models mandates a minimum of 30 GB of GPU memory and may span up to eight hours of computational runtime. Section A.1 in Appendix A contains details about the compute resources needed for this work.

We have observed that one of the CoNLL metrics, BCUB (BAGGA, 1998), may fail to generate meaningful scores on instances containing splitted antecedants in the key coreference chains. For instance consider the following paragraph:

> ***Thatcher***$_a$ *grew up in Lincolnshire whereas* ***Gandhi***$_b$ *was raised in Allahabad.* ***Both***$_c$ *become powerful figures.* ***They***$_d$ *locked horns in 1983. The world watched as* ***the Iron Lady of India***$_e$ *stood against* ***the Iron Lady of UK***$_f$*.*

If a system response (predictions) is identical to the key (ground-truth), then the BCUB recall score would be 1.25. Furthermore, the LEA metric, introduced as an alternative to CoNLL metrics by Moosavi and Strube (2016) also yields imperfect scores for the above example. The formulation of LEA metric gives a score of 1.16 for recall, precision, and F1 when the ground-truth is used as the key and response. This underscores the necessity for an evaluation metric capable of effectively handling split antecedents in coreference resolution. Furthermore, the presence of split antecedents not only highlights a significant deficiency in current coreference resolution evaluation metrics but also poses challenges in the training of existing coreference resolution models. This challenge stems from architectural limitations in these models, which permit only one antecedent per mention, whereas split antecedents refer to multiple antecedents earlier in the discourse.

6. Conclusion

Numerous research initiatives have tackled the automated resolution of coreferences in South Asian languages. However, a notable absence of publicly available resources and models still persists in this domain. This study addresses this gap by introducing TransMuCoRes, a Translated dataset designed for Multilingual Coreference Resolution. We also release checkpoints of two off-the-shelf methods fine-tuned on TransMyCoRes and the golden set of Hindi. Our observations indicate that fine-tuning the wl-coref method is feasible for specific South Asian languages that have an available dependency parser. Notably, it outperforms fast-coref in the languages on which it was fine-tuned.

6.1. Limitations and Future Work

This work encounters a significant constraint concerning the potential for transferring bias during the translation of the English dataset into various target languages (Cao and Daumé III, 2020). Furthermore, substantial computational resources are essential to replicate this study. The assessment of coreference resolution models for languages other than Hindi posed a significant challenge attributable to the scarcity of gold annotated resources. We acknowledge the constrained scope of the dataset available for evaluating languages other than Hindi.

The observations presented here are contingent on the specific data splits chosen from LitBank and the dataset by Mujadia et al. (2016). To validate these findings, cross-validation experiments are required. In the future, we aim to expand the dataset to encompass additional low-resource languages supported by NLLB models. Additionally, there is a pressing need for the development of a new evaluation metric capable of accurately assessing coreference clusters that involve split antecedents.

There are some future directions that needs to be explored to improve the performance of wl-coref model for other languages. Data preprocessing for training the wl-coref model requires dependency parsing, primarily to identify the syntactic head-word of each mention. In cases where a dependency parsing tool is not accessible for specific languages, alternative approaches can be investigated to identify the head-word of a mention[5]. Accurate identification of head-words would facilitate fine-tuning the wl-coref model across diverse languages, thereby enhancing its efficacy.

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8. Bibliographical References

A Akilandeswari and Sobha Lalitha Devi. 2012. Resolution for pronouns in tamil using crf. In

[5] https://github.com/vdobrovolskii/wl-coref/issues/12

Proceedings of the Workshop on Machine Translation and Parsing in Indian Languages, pages 103–112.

Abdulrahman Aloraini, Juntao Yu, and Massimo Poesio. 2020. Neural coreference resolution for arabic. In *Proceedings of the Third Workshop on Computational Models of Reference, Anaphora and Coreference*, pages 99–110.

A BAGGA. 1998. Algorithms for scoring coreference chains. In *Proc. Linguistic Coreference Workshop at the first Conf. on Language Resources and Evaluation (LREC), Granada, Spain, May 1998*.

David Bamman, Olivia Lewke, and Anya Mansoor. 2020. An annotated dataset of coreference in english literature. In *Proceedings of the 12th Language Resources and Evaluation Conference*, pages 44–54.

Iz Beltagy, Matthew E Peters, and Arman Cohan. 2020. Longformer: The long-document transformer. *arXiv preprint arXiv:2004.05150*.

Santanu Bhattacharjee, Rejwanul Haque, Gideon Maillette de Buy Wenniger, and Andy Way. 2020. Investigating query expansion and coreference resolution in question answering on bert. In *Natural Language Processing and Information Systems: 25th International Conference on Applications of Natural Language to Information Systems, NLDB 2020, Saarbrücken, Germany, June 24–26, 2020, Proceedings*, pages 47–59. Springer.

Bernd Bohnet, Chris Alberti, and Michael Collins. 2023. Coreference resolution through a seq2seq transition-based system. *Transactions of the Association for Computational Linguistics*, 11:212–226.

Yang Trista Cao and Hal Daumé III. 2020. Toward gender-inclusive coreference resolution. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4568–4595.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Édouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised cross-lingual representation learning at scale. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8440–8451.

Praveen Dakwale, Vandan Mujadia, and Dipti Misra Sharma. 2013. A hybrid approach for anaphora resolution in hindi. In *Proceedings of the Sixth International Joint Conference on Natural Language Processing*, pages 977–981.

Berenstein David. 2022. Crosslingual Coreference - a multi-lingual approach to AllenNLP CoReference Resolution along with a wrapper for spaCy.

VENEETA Dayal and ANOOP Mahajan. 2004. Clause structure in south asian languages: general introduction. *Clause structure in South Asian Languages*, pages 1–11.

Sobha Lalitha Devi, Vijay Sundar Ram, and Pattabhi RK Rao. 2014. A generic anaphora resolution engine for indian languages. In *Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers*, pages 1824–1833.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 NAACL*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Vladimir Dobrovolskii. 2021. Word-level coreference resolution. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 7670–7675.

Kamlesh Dutta, Nupur Prakash, and Saroj Kaushik. 2008. Resolving pronominal anaphora in hindi using hobbs algorithm. *Web Journal of Formal Computation and Cognitive Linguistics*, 1(10):5607–11.

Ethnologue. 2021. What are the top 200 most spoken languages?

Ankur Gandhe, Rashmi Gangadharaiah, Karthik Visweswariah, and Ananthakrishnan Ramanathan. 2011. Handling verb phrase morphology in highly inflected indian languages for machine translation. In *Proceedings of 5th international joint conference on natural language processing*, pages 111–119.

Aria Haghighi and Dan Klein. 2009. Simple coreference resolution with rich syntactic and semantic features. In *Proceedings of the 2009 conference on empirical methods in natural language processing*, pages 1152–1161.

Jerry R. Hobbs. 1978. Resolving pronoun references. *Lingua*, 44(4):311–338.

Hemanth Reddy Jonnalagadda and Radhika Mamidi. 2015. Resolution of pronominal anaphora for telugu dialogues. In *Proceedings of the 12th international conference on natural language processing*, pages 183–188.

Mandar Joshi, Danqi Chen, Yinhan Liu, Daniel S. Weld, Luke Zettlemoyer, and Omer Levy. 2020. SpanBERT: Improving pre-training by representing and predicting spans. *Transactions of the Association for Computational Linguistics*, 8:64–77.

Mandar Joshi, Omer Levy, Luke Zettlemoyer, and Daniel S Weld. 2019. Bert for coreference resolution: Baselines and analysis. In *Proceedings of the 2019 EMNLP-IJCNLP*, pages 5803–5808.

Kalpana Khandale and C. Namrata Mahender. 2019a. Rule-based design for anaphora resolution of marathi sentence. In *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, pages 1–7.

Kalpana Khandale and C Namrata Mahender. 2019b. Rule-based design for anaphora resolution of marathi sentence. In *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, pages 1–7. IEEE.

Yuval Kirstain, Ori Ram, and Omer Levy. 2021. Coreference resolution without span representations. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 14–19.

Sandra Kübler and Desislava Zhekova. 2011. Singletons and coreference resolution evaluation. In *Proceedings of the International Conference Recent Advances in Natural Language Processing 2011*, pages 261–267.

Gourab Kundu, Avirup Sil, Radu Florian, and Wael Hamza. 2018. Neural cross-lingual coreference resolution and its application to entity linking. *arXiv preprint arXiv:1806.10201*.

Shalom Lappin and Herbert J Leass. 1994. An algorithm for pronominal anaphora resolution. *Computational linguistics*, 20(4):535–561.

Kusum Lata, Pardeep Singh, and Kamlesh Dutta. 2023. Semi-automatic annotation for mentions in hindi text. *SN Computer Science*, 4(5):515.

Kenton Lee, Luheng He, Mike Lewis, and Luke Zettlemoyer. 2017. End-to-end neural coreference resolution. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 188–197, Copenhagen, Denmark. Association for Computational Linguistics.

Kenton Lee, Luheng He, and Luke Zettlemoyer. 2018. Higher-order coreference resolution with coarse-to-fine inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 687–692, New Orleans, Louisiana. Association for Computational Linguistics.

Tianyu Liu, Yuchen Eleanor Jiang, Nicholas Monath, Ryan Cotterell, and Mrinmaya Sachan. 2022. Autoregressive structured prediction with language models. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 993–1005.

Pohanyar Hejratullah Mobashir. 2021. Research of current common languages in afghanistan. *Randwick International of Education and Linguistics Science Journal*, 2(4):555–559.

Nafise Sadat Moosavi and Michael Strube. 2016. Which coreference evaluation metric do you trust? a proposal for a link-based entity aware metric. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 632–642.

Shon Otmazgin, Arie Cattan, and Yoav Goldberg. 2022. F-coref: Fast, accurate and easy to use coreference resolution. In *Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing: System Demonstrations*, pages 48–56.

Shon Otmazgin, Arie Cattan, and Yoav Goldberg. 2023. Lingmess: Linguistically informed multi expert scorers for coreference resolution. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, pages 2744–2752.

Peng Qi, Yuhao Zhang, Yuhui Zhang, Jason Bolton, and Christopher D. Manning. 2020. Stanza: A Python natural language processing toolkit for many human languages. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*.

Vijay Sundar Ram and Sobha Lalitha Devi. 2017. Co-reference resolution in tamil text. In *Proceedings of the 14th International Conference on Natural Language Processing (ICON-2017)*, pages 392–401.

Vijay Sundar Ram and Sobha Lalitha Devi. 2020. Handling noun-noun coreference in tamil. In *Proceedings of the WILDRE5–5th Workshop on Indian Language Data: Resources and Evaluation*, pages 20–24.

Marta Recasens, Marie-Catherine De Marneffe, and Christopher Potts. 2013. The life and death of discourse entities: Identifying singleton mentions. In *Proceedings of the 2013 conference of the North American chapter of the association for computational linguistics: human language technologies*, pages 627–633.

Apurbalal Senapati and Utpal Garain. 2013. Guitar-based pronominal anaphora resolution in bengali. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 126–130.

Michael C. Shapiro. 2003. Hindi. In George Cardona and Dhanesh Jain, editors, *The Indo-Aryan Languages*, Routledge Language Family Series, pages 250–285. London & New York: Routledge, London.

Kumar Shridhar, Nicholas Monath, Raghuveer Thirukovalluru, Alessandro Stolfo, Manzil Zaheer, Andrew Mccallum, and Mrinmaya Sachan. 2023. Longtonotes: Ontonotes with longer coreference chains. In *Findings of the Association for Computational Linguistics: EACL 2023*, pages 1398–1412.

Utpal Kumar Sikdar, Asif Ekbal, and Sriparna Saha. 2016. A generalized framework for anaphora resolution in indian languages. *Knowledge-Based Systems*, 109:147–159.

Sandhya Singh, Kevin Patel, and Pushpak Bhattacharyya. 2020. Attention based anaphora resolution for code-mixed social media text for hindi language. In *FIRE (Working Notes)*, pages 780–787.

Smriti Singh and Vaijayanthi M Sarma. 2011. Verbal inflection in hindi: A distributed morphology approach. In *Proceedings of the 25th Pacific Asia Conference on Language, Information and Computation*, pages 283–292.

Ankur Sonawane, Sujeet Kumar Vishwakarma, Bhavana Srivastava, and Anil Kumar Singh. 2020. Generating inflectional errors for grammatical error correction in hindi. In *Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing: Student Research Workshop*, pages 165–171.

Shubham Toshniwal, Sam Wiseman, Allyson Ettinger, Karen Livescu, and Kevin Gimpel. 2020. Learning to Ignore: Long Document Coreference with Bounded Memory Neural Networks. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 8519–8526, Online. Association for Computational Linguistics.

Shubham Toshniwal, Patrick Xia, Sam Wiseman, Karen Livescu, and Kevin Gimpel. 2021. On Generalization in Coreference Resolution. In *CRAC (EMNLP)*.

Ralph Weischedel, Martha Palmer, Mitchell Marcus, Eduard Hovy, Sameer Pradhan, Lance Ramshaw, Nianwen Xue, Ann Taylor, Jeff Kaufman, Michelle Franchini, et al. 2013. Ontonotes release 5.0 ldc2013t19. *Linguistic Data Consortium, Philadelphia, PA*, 23.

Lesly Miculicich Werlen and James Henderson. 2022. Graph refinement for coreference resolution. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 2732–2742.

Patrick Xia and Benjamin Van Durme. 2021. Moving on from OntoNotes: Coreference resolution model transfer. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 5241–5256, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Liyan Xu and Jinho D. Choi. 2020. Revealing the myth of higher-order inference in coreference resolution. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 8527–8533, Online. Association for Computational Linguistics.

Juntao Yu, Alexandra Uma, and Massimo Poesio. 2020. A cluster ranking model for full anaphora resolution. In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pages 11–20, Marseille, France. European Language Resources Association.

Pengfei Zhu, Zhuosheng Zhang, Jiangtong Li, Yafang Huang, and Hai Zhao. 2018. Lingke: A fine-grained multi-turn chatbot for customer service. *arXiv preprint arXiv:1808.03430*.

9. Language Resource References

Zi-Yi Dou and Graham Neubig. 2021. Word alignment by fine-tuning embeddings on parallel corpora. In *Conference of the European Chapter of the Association for Computational Linguistics (EACL)*.

Vandan Mujadia, Palash Gupta, and Dipti Misra Sharma. 2016. Coreference annotation scheme and relation types for hindi. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC'16)*, pages 161–168.

Silviu Paun, Juntao Yu, Nafise Sadat Moosavi, and Massimo Poesio. 2022. Scoring coreference chains with split-antecedent anaphors.

Masoud Jalili Sabet, Philipp Dufter, François Yvon, and Hinrich Schütze. 2020. Simalign: High quality word alignments without parallel training data using static and contextualized embeddings. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1627–1643.

NLLB Team, Marta R. Costa-jussà, James Cross, Onur Çelebi, Maha Elbayad, Kenneth Heafield, Kevin Heffernan, Elahe Kalbassi, Janice Lam, Daniel Licht, Jean Maillard, Anna Sun, Skyler Wang, Guillaume Wenzek, Al Youngblood, Bapi Akula, Loic Barrault, Gabriel Mejia Gonzalez, Prangthip Hansanti, John Hoffman, Semarley Jarrett, Kaushik Ram Sadagopan, Dirk Rowe, Shannon Spruit, Chau Tran, Pierre Andrews, Necip Fazil Ayan, Shruti Bhosale, Sergey Edunov, Angela Fan, Cynthia Gao, Vedanuj Goswami, Francisco Guzmán, Philipp Koehn, Alexandre Mourachko, Christophe Ropers, Safiyyah Saleem, Holger Schwenk, and Jeff Wang. 2022. No language left behind: Scaling human-centered machine translation.

Language	Translation Sanity-check	
	Passed	Failed
asm_Beng	102828	3
awa_Deva	102828	3
ben_Beng	102825	6
bho_Deva	102829	2
bod_Tibt	102828	3
dzo_Tibt	102827	4
guj_Gujr	102828	3
hin_Deva	102827	4
hne_Deva	102829	2
kan_Knda	102828	3
kas_Arab	102831	0
mag_Deva	102827	4
mai_Deva	102828	3
mal_Mlym	102826	5
mar_Deva	102826	5
mni_Beng	102829	2
mya_Mymr	102827	4
npi_Deva	102828	3
ory_Orya	102829	2
pan_Guru	102829	2
pbt_Arab	102830	1
prs_Arab	102827	4
sat_Beng	102828	3
sin_Sinh	102829	2
snd_Arab	102817	14
tam_Taml	102827	4
tel_Telu	102823	8
tgk_Cyrl	102826	5
uig_Arab	102829	2
urd_Arab	102828	3
uzn_Latn	102829	2
Total	3187650	111

Table 7: Number of translated sentences that passed/failed the sanity-check. The sanity-check was composed of identifying whether the translated sentence is a repetitive sequence of punctuation's or not.

A. Appendix

A.1. Compute Resources Needed

The GPU memory footprint of awesome-align model, *facebook/nllb-200-1.3B* model, and *facebook/nllb-200-3.3B* model is 2GB, 7GB, and 14GB, respectively. On average, the translation model, and alignment model takes 3 seconds, and 30 milliseconds, respectively for each sentence. Therefore, the estimated time to re-construct TransMuCoRes is nearly 3 months on a single GPU. During fine-tuning phase, the memory footprint of wl-coref model, and fast-coref model is 30GB, and 8GB, respectively. Whereas, during inference phase, it is 5GB and 1 GB, respectively. The wl-coref model takes 45 mins per epoch whereas fast-coref runs for 100K steps in 6 hours.

Language	Mentions (223583)		
	Aligned	Misaligned	Non-aligned
asm_Beng	66.1%	15.3%	18.6%
awa_Deva	71.3%	15%	13.7%
ben_Beng	87.4%	6.7%	5.8%
bho_Deva	72.6%	14.5%	12.9%
bod_Tibt	69.7%	4.5%	25.7%
dzo_Tibt	62.8%	7.9%	29.3%
guj_Gujr	86.7%	7.1%	6.2%
hin_Deva	87%	7.8%	5.1%
hne_Deva	70.8%	14.6%	14.6%
kan_Knda	86.3%	6.6%	7.1%
kas_Arab	59.8%	18.7%	21.4%
mag_Deva	73.6%	13%	13.4%
mai_Deva	69.7%	13.8%	16.4%
mal_Mlym	78.9%	8.6%	12.5%
mar_Deva	84.5%	7.1%	8.5%
mni_Beng	57%	19.7%	23.3%
mya_Mymr	79.8%	7.7%	12.4%
npi_Deva	86.1%	6.8%	7.1%
ory_Orya	46.1%	10%	43.9%
pan_Guru	85.2%	9.4%	5.4%
pbt_Arab	58%	22.4%	19.6%
prs_Arab	82.9%	8.4%	8.8%
sat_Beng	52.3%	12.7%	34.9%
sin_Sinh	48%	10.1%	41.9%
snd_Arab	56.7%	22.3%	21.1%
tam_Taml	83.5%	7.4%	9.1%
tel_Telu	84.7%	7.6%	7.6%
tgk_Cyrl	80.9%	8.9%	10.2%
uig_Arab	57.2%	17.9%	24.9%
urd_Arab	83.4%	10.9%	5.7%
uzn_Latn	77.4%	8.4%	14.1%
Total	72.5%	11.4%	16.2%

Table 8: Performance of word-alignment tool on various languages. A mention is a continuous span of words. It is considered to be aligned if all the words of the mention are aligned to a continuous span of words in the target language. If it is aligned to a discontinuous span of words in the target language then it is called misaligned. And if a mention is not aligned to any word in the target language then it is considered as non-aligned.

Language	#sents	#mentions	#coreference clusters	#split antecedants	#singletons	#docs
asm_Beng	(58706 , 7174 , 8194)	(113275 , 13882 , 16387)	(35734 , 4671 , 5182)	(2559 , 337 , 387)	(12986 , 1731 , 2089)	(2835 , 352 , 365)
awa_Deva	(59296 , 7257 , 8212)	(123270 , 15298 , 18003)	(36869 , 4791 , 5333)	(1627 , 176 , 200)	(11965 , 1542 , 1958)	(2840 , 352 , 366)
ben_Beng	(63812 , 7830 , 8862)	(151825 , 18931 , 22395)	(39523 , 5171 , 5834)	(1116 , 115 , 123)	(8475 , 1136 , 1643)	(2843 , 352 , 366)
bho_Deva	(59942 , 7378 , 8344)	(125719 , 15709 , 18574)	(36989 , 4897 , 5436)	(1317 , 140 , 169)	(11967 , 1613 , 1972)	(2837 , 352 , 363)
bod_Tibt	(58372 , 7157 , 8046)	(84334 , 10549 , 12085)	(36918 , 4791 , 5414)	(22268 , 2491 , 3085)	(12046 , 1603 , 2104)	(2840 , 351 , 363)
dzo_Tibt	(56040 , 6837 , 7684)	(95515 , 11736 , 13648)	(35182 , 4551 , 5059)	(11767 , 1276 , 1584)	(13404 , 1795 , 2183)	(2827 , 351 , 364)
guj_Gujr	(63687 , 7805 , 8835)	(150276 , 18687 , 22182)	(39279 , 5125 , 5788)	(1135 , 112 , 130)	(8744 , 1142 , 1623)	(2843 , 352 , 366)
hin_Deva	(63841 , 7820 , 8883)	(151922 , 18982 , 22373)	(39129 , 5157 , 5775)	(624 , 58 , 56)	(8862 , 1198 , 1689)	(2843 , 352 , 366)
hne_Deva	(59393 , 7304 , 8270)	(122714 , 15269 , 17977)	(36854 , 4856 , 5375)	(1378 , 146 , 214)	(12232 , 1621 , 1983)	(2843 , 352 , 364)
kan_Knda	(63815 , 7822 , 8897)	(149004 , 18501 , 22007)	(39588 , 5172 , 5862)	(1645 , 171 , 215)	(8515 , 1143 , 1653)	(2843 , 352 , 365)
kas_Arab	(55735 , 6733 , 7765)	(102470 , 12520 , 14932)	(34261 , 4433 , 4956)	(2476 , 270 , 321)	(14038 , 1806 , 2150)	(2834 , 350 , 363)
mag_Deva	(60451 , 7403 , 8409)	(127402 , 15940 , 18708)	(37356 , 4922 , 5470)	(1420 , 146 , 179)	(11762 , 1578 , 2001)	(2841 , 352 , 365)
mai_Deva	(59284 , 7260 , 8243)	(120323 , 14820 , 17608)	(36704 , 4760 , 5341)	(1927 , 202 , 280)	(12422 , 1588 , 2034)	(2838 , 351 , 365)
mal_Mlym	(62141 , 7633 , 8622)	(133610 , 16648 , 19613)	(38726 , 5086 , 5678)	(3451 , 360 , 459)	(9749 , 1355 , 1786)	(2842 , 352 , 364)
mar_Deva	(63279 , 7732 , 8783)	(145616 , 18050 , 21406)	(39152 , 5103 , 5748)	(1557 , 165 , 184)	(9199 , 1225 , 1710)	(2843 , 352 , 365)
mni_Beng	(54556 , 6722 , 7642)	(96202 , 11657 , 13953)	(32757 , 4266 , 4714)	(3230 , 383 , 451)	(13896 , 1861 , 2143)	(2829 , 351 , 362)
mya_Mymr	(62366 , 7633 , 8659)	(131466 , 16418 , 19073)	(38975 , 5088 , 5756)	(6403 , 707 , 935)	(9412 , 1208 , 1802)	(2844 , 351 , 366)
npi_Deva	(63471 , 7784 , 8817)	(149191 , 18586 , 22003)	(39359 , 5141 , 5817)	(1294 , 134 , 151)	(8819 , 1165 , 1671)	(2841 , 352 , 365)
ory_Orya	(47958 , 5775 , 6626)	(78750 , 9367 , 11132)	(29454 , 3844 , 4162)	(2720 , 315 , 443)	(14003 , 1905 , 2079)	(2822 , 348 , 362)
pan_Guru	(63448 , 7776 , 8842)	(148484 , 18395 , 21907)	(38776 , 5035 , 5705)	(701 , 85 , 83)	(9575 , 1200 , 1733)	(2839 , 352 , 366)
pbt_Arab	(54706 , 6582 , 7599)	(100295 , 12038 , 14467)	(32813 , 4211 , 4687)	(1772 , 225 , 253)	(13898 , 1800 , 2125)	(2826 , 350 , 363)
prs_Arab	(62579 , 7650 , 8722)	(144778 , 17816 , 21260)	(39040 , 5113 , 5729)	(1163 , 138 , 203)	(9825 , 1373 , 1807)	(2844 , 352 , 365)
sat_Beng	(50952 , 6129 , 6949)	(89870 , 10704 , 12679)	(31207 , 4049 , 4439)	(2676 , 324 , 405)	(13883 , 1835 , 2108)	(2827 , 349 , 361)
sin_Sinh	(48903 , 5930 , 6743)	(81864 , 9910 , 11615)	(30266 , 3947 , 4259)	(2866 , 364 , 439)	(13875 , 1867 , 2056)	(2818 , 350 , 362)
snd_Arab	(54718 , 6673 , 7596)	(98325 , 11871 , 14214)	(32806 , 4237 , 4691)	(2141 , 289 , 350)	(14142 , 1825 , 2153)	(2822 , 350 , 363)
tam_Taml	(63313 , 7765 , 8798)	(143782 , 17914 , 21120)	(39279 , 5127 , 5795)	(1774 , 162 , 223)	(9165 , 1197 , 1711)	(2842 , 352 , 365)
tel_Telu	(63707 , 7809 , 8868)	(146249 , 18198 , 21652)	(39306 , 5150 , 5820)	(1738 , 176 , 201)	(9062 , 1230 , 1749)	(2844 , 352 , 366)
tgk_Cyrl	(62447 , 7650 , 8670)	(139803 , 17348 , 20413)	(38981 , 5064 , 5701)	(2052 , 241 , 286)	(9693 , 1301 , 1742)	(2843 , 352 , 365)
uig_Arab	(54313 , 6611 , 7563)	(96106 , 11645 , 13899)	(33532 , 4337 , 4843)	(3922 , 457 , 519)	(14085 , 1833 , 2187)	(2831 , 350 , 362)
urd_Arab	(63010 , 7743 , 8759)	(146133 , 18133 , 21421)	(38494 , 5053 , 5617)	(616 , 68 , 64)	(10185 , 1364 , 1826)	(2840 , 352 , 365)
uzn_Latn	(61642 , 7534 , 8564)	(132967 , 16561 , 19387)	(38597 , 5041 , 5678)	(2333 , 272 , 352)	(10133 , 1359 , 1809)	(2842 , 352 , 366)
Total	(1839883 , 224911 , 255466)	(3821540 , 472083 , 558093)	(1135906 , 148189 , 165664)	(93668 , 10505 , 12944)	(350017 , 46399 , 59279)	(87946 , 10890 , 11294)

Table 9: Data statistics of TransMuCoRes for each language. The numbers written inside round brackets represents the (train , development , test) splits.

				Mentions			MUC			B^3			CEAFe			LEA			CoNLL
				P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	F1
wl-coref (Dobrovolskii, 2021)	5 langs	mbert	dev	65	**75**	70	57	67	61	43	54	48	46	52	49	39	49	44	53
			test	68	**77**	72	61	70	65	44	**55**	49	46	50	48	41	**51**	45	54
		xlmr	dev	**70**	**75**	**72**	**63**	**68**	**65**	**50**	**55**	**52**	**51**	**55**	**53**	**46**	**50**	**48**	**57**
			test	**72**	**77**	**75**	**66**	**71**	**69**	**52**	**55**	**53**	**50**	**54**	**52**	**48**	**51**	**50**	**58**
	All langs	mbert	dev	40	66	50	32	56	41	23	**46**	31	28	42	33	20	**40**	27	35
			test	42	68	52	34	59	44	23	**47**	31	27	40	33	21	**42**	28	36
		xlmr	dev	48	60	53	40	51	45	31	40	35	**34**	42	37	27	36	31	39
			test	50	62	55	42	54	47	31	41	35	**33**	41	37	28	37	32	40
fast-coref (Toshniwal et al., 2021)	All langs	mbert	dev	47	**73**	57	41	59	48	30	41	35	25	52	34	26	36	30	39
			test	50	74	60	44	62	52	31	42	35	25	51	33	27	37	32	40
		xlmr	dev	**51**	**73**	**60**	**46**	**61**	**52**	**35**	44	**39**	29	**56**	**38**	**32**	39	**35**	**43**
			test	**54**	**75**	**63**	**49**	**64**	**56**	**36**	44	**40**	29	**55**	**38**	**33**	40	**36**	**44**

Table 10: Performance of wl-coref (Dobrovolskii, 2021) and fast-coref (Toshniwal et al., 2021) while ignoring the singeltons during the evaluation phase. It can be seen that the performance improves for both the models. Indicating that both the models struggles in capturing the singletons.

Language	fast-coref (Toshniwal et al., 2021) vs wl-coref (Dobrovolskii, 2021) on fine-tuned xlmr													
	Split	Mentions F1	MUC F1	B^3 F1	CEAFe F1	LEA F1	CoNLL F1	Split	Mentions F1	MUC F1	B^3 F1	CEAFe F1	LEA F1	CoNLL F1
asm_Beng	DEVELOPMENT	47 vs 46	38 vs 35	26 vs 24	28 vs 29	22 vs 19	31 vs 29	TEST	49 vs 47	41 vs 37	26 vs 23	28 vs 29	22 vs 19	32 vs 30
awa_Deva		51 vs 44	42 vs 32	29 vs 25	33 vs 32	25 vs 20	35 vs 30		53 vs 44	45 vs 33	29 vs 23	33 vs 31	25 vs 19	35 vs 29
ben_Beng		75 vs 74	67 vs 66	52 vs 53	51 vs 52	48 vs 48	57 vs 57		78 vs 76	71 vs 70	53 vs 54	51 vs 52	50 vs 51	59 vs 59
bho_Deva		54 vs 42	46 vs 33	32 vs 24	34 vs 29	28 vs 20	37 vs 29		56 vs 45	49 vs 35	32 vs 24	33 vs 29	28 vs 20	38 vs 29
bod_Tibt		62 vs 7	46 vs 3	17 vs 2	13 vs 5	13 vs 2	26 vs 3		63 vs 7	51 vs 3	19 vs 3	14 vs 5	16 vs 2	28 vs 4
dzo_Tibt		20 vs 4	15 vs 3	9 vs 2	7 vs 4	7 vs 1	10 vs 3		21 vs 6	16 vs 4	10 vs 3	9 vs 5	8 vs 2	12 vs 4
guj_Gujr		74 vs 74	66 vs 65	50 vs 52	50 vs 52	46 vs 48	55 vs 57		76 vs 76	69 vs 68	51 vs 52	49 vs 52	47 vs 48	56 vs 58
hin_Deva		75 vs 75	68 vs 68	52 vs 55	51 vs 55	48 vs 51	57 vs 59		77 vs 78	71 vs 72	53 vs 56	51 vs 55	50 vs 53	58 vs 61
hne_Deva		49 vs 40	41 vs 29	29 vs 21	34 vs 28	25 vs 17	34 vs 26		50 vs 42	43 vs 31	28 vs 22	33 vs 28	25 vs 18	35 vs 27
kan_Knda		73 vs 72	65 vs 63	50 vs 51	50 vs 52	46 vs 46	55 vs 55		76 vs 74	68 vs 67	51 vs 52	49 vs 52	47 vs 48	56 vs 57
kas_Arab		35 vs 14	27 vs 8	18 vs 7	22 vs 13	14 vs 6	22 vs 9		37 vs 15	30 vs 9	18 vs 7	21 vs 13	15 vs 5	23 vs 9
mag_Deva		55 vs 48	47 vs 38	33 vs 28	34 vs 33	29 vs 23	38 vs 33		58 vs 51	51 vs 41	33 vs 28	34 vs 32	30 vs 24	39 vs 34
mai_Deva		50 vs 40	42 vs 32	29 vs 23	32 vs 27	25 vs 19	34 vs 27		53 vs 41	45 vs 34	30 vs 23	31 vs 26	26 vs 19	36 vs 27
mal_Mlym		67 vs 66	58 vs 56	43 vs 44	44 vs 48	39 vs 39	48 vs 49		70 vs 68	62 vs 60	45 vs 46	44 vs 48	40 vs 41	50 vs 51
mar_Deva		73 vs 72	65 vs 64	50 vs 52	49 vs 52	45 vs 48	54 vs 56		75 vs 74	68 vs 68	51 vs 53	48 vs 51	47 vs 49	56 vs 57
mni_Beng		32 vs 10	24 vs 4	14 vs 3	16 vs 7	10 vs 2	18 vs 5		35 vs 11	28 vs 6	14 vs 3	15 vs 6	11 vs 2	19 vs 5
mya_Mymr		62 vs 54	52 vs 42	37 vs 33	39 vs 39	32 vs 28	43 vs 38		64 vs 56	55 vs 46	37 vs 32	38 vs 39	32 vs 28	43 vs 39
npi_Deva		75 vs 74	68 vs 66	53 vs 53	52 vs 53	49 vs 49	57 vs 57		78 vs 76	72 vs 70	54 vs 55	52 vs 54	51 vs 51	59 vs 60
ory_Orya		25 vs 22	19 vs 13	11 vs 8	13 vs 13	9 vs 5	14 vs 11		28 vs 23	22 vs 15	11 vs 8	13 vs 13	9 vs 5	15 vs 12
pan_Guru		72 vs 71	64 vs 63	48 vs 50	48 vs 51	44 vs 45	53 vs 54		74 vs 73	68 vs 67	49 vs 51	48 vs 50	46 vs 47	55 vs 56
pbt_Arab		36 vs 29	31 vs 21	20 vs 13	22 vs 19	17 vs 10	24 vs 18		39 vs 31	34 vs 23	20 vs 13	22 vs 20	18 vs 10	25 vs 19
prs_Arab		70 vs 65	63 vs 56	47 vs 44	47 vs 47	43 vs 39	52 vs 49		72 vs 67	66 vs 60	47 vs 45	45 vs 45	44 vs 40	53 vs 50
sat_Beng		13 vs 5	10 vs 2	6 vs 2	5 vs 3	5 vs 1	7 vs 2		15 vs 6	12 vs 4	6 vs 2	5 vs 4	5 vs 2	8 vs 3
sin_Sinh		24 vs 22	18 vs 13	11 vs 8	14 vs 14	9 vs 5	14 vs 12		27 vs 23	22 vs 15	12 vs 8	14 vs 14	10 vs 6	16 vs 12
snd_Arab		33 vs 31	26 vs 22	16 vs 14	19 vs 20	13 vs 10	21 vs 18		34 vs 32	28 vs 24	16 vs 14	20 vs 20	13 vs 10	21 vs 19
tam_Taml		71 vs 71	63 vs 63	48 vs 51	48 vs 53	44 vs 46	53 vs 55		73 vs 73	66 vs 66	49 vs 51	47 vs 51	45 vs 47	54 vs 56
tel_Telu		72 vs 72	64 vs 64	49 vs 52	48 vs 52	45 vs 47	54 vs 56		74 vs 74	68 vs 68	51 vs 54	47 vs 52	47 vs 50	55 vs 58
tgk_Cyrl		62 vs 17	52 vs 11	37 vs 8	38 vs 14	33 vs 7	42 vs 11		64 vs 16	55 vs 11	38 vs 7	37 vs 13	34 vs 6	43 vs 10
uig_Arab		23 vs 25	15 vs 14	9 vs 10	13 vs 16	7 vs 6	12 vs 13		23 vs 26	17 vs 16	9 vs 10	12 vs 16	7 vs 6	13 vs 14
urd_Arab		71 vs 71	63 vs 64	48 vs 51	48 vs 52	44 vs 47	53 vs 56		73 vs 73	67 vs 67	48 vs 51	47 vs 51	45 vs 48	54 vs 56
uzn_Latn		64 vs 60	54 vs 50	40 vs 39	44 vs 45	36 vs 35	46 vs 45		65 vs 62	57 vs 53	40 vs 39	42 vs 43	36 vs 35	46 vs 45
Mujadia et al. (2016)		51 vs 79	45 vs 74	36 vs 67	36 vs 66	32 vs 64	39 vs 69		56 vs 80	51 vs 76	40 vs 69	35 vs 66	35 vs 66	42 vs 70
Overall		60 vs 53	52 vs 45	39 vs 35	38 vs 37	34 vs 31	43 vs 39		63 vs 55	56 vs 47	40 vs 35	38 vs 37	36 vs 32	44 vs 40

Table 11: Language wise performance of wl-coref (Dobrovolskii, 2021) and fast-coref (Toshniwal et al., 2021) in absence of singletons. Notice that performance improves across languages. Indicating that both the models struggles to capture singletons across all languages. Hence advocating the need for coreference resolution models with higher recall in mention detection phase.