Welcome to the Modern World of Pronouns: Identity-Inclusive Natural Language Processing beyond Gender

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Abstract

Trigger warning: This paper contains examples that contain transphobic language.

The world of pronouns is changing - from a closed word class with few members to an open set of terms to reflect identities. However, Natural Language Processing (NLP) barely reflects this linguistic shift, resulting in the possible exclusion of non-binary users, even though recent work outlined the harms of gender-exclusive language technology. The current modeling of 3rd person pronouns is particularly problematic. It largely ignores various phenomena like neopronouns, i.e., novel pronoun sets that are not (yet) widely established. This omission contributes to the discrimination of marginalized and underrepresented groups, e.g., nonbinary individuals. It thus prevents gender equality, one of the UN's sustainable development goals (goal 5). Further, other identityexpressions beyond gender are ignored by current NLP technology. This paper provides an overview of 3rd person pronoun issues for NLP. Based on our observations and ethical considerations, we define a series of five desiderata for modeling pronouns in language technology, which we validate through a survey. We evaluate existing and novel modeling approaches w.r.t. these desiderata qualitatively and quantify the impact of a more discrimination-free approach on an established benchmark dataset.

1 Introduction

Pronouns are an essential component of many languages and often one of the most frequent word classes. Accordingly, NLP has long studied tasks related to them, e.g., pronoun resolution (e.g., Hobbs, 1978). Simplistically, they can be defined as "a word (such as I, he, she, you, it, we, or they) that is used instead of a noun or noun phrase".1

Nom.	Acc.	Poss. (dep.)	Poss. (indep.)	Reflexive						
Gendered Pronouns										
he	him	his	his	himself						
she	her	her	hers	herself						
Gender-Neutral Pronouns										
they	them	their	theirs	themself						
Neopron	ouns									
thon	thon	thons	thons	thonself						
e	em	es	ems	emself						
xe	xem	xyr	xyrs	xemself						
ey	em	eir	eirs	emself						
e	em	eir	eirs	emself						
ze	zir	zir	zirs	zirself						
•••										
Nounselj	^f Pronouns									
star	star	stars	stars	starself						
vam	vamp	vamps	vamps	vampself						
•••										
Emojisel	f Pronoun:	S								
6		🏂 s	S S	i self						
6	C.S	S S	(XS	self						
•••										
Numbers	self Pronou	ins								
0	0	0s	0s	0self						
$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$ s	$\frac{1}{3}$ s	$\frac{1}{3}$ self						
	~	-	-	-						
Nameself Pronouns										
John	John	Johns	Johns	Johnself						

Table 1: Non-exhaustive overview of phenomena related to third-person pronoun usage in English.

Linguistic studies have pointed out the complexity of pronouns, though (e.g., Postal et al., 1969; McKay, 1993). Pronouns can carry demographic information – in English, for example, information about the *number* of referents and a single referent's (grammatical) *gender*.² Pronouns can convey even more information in other, non-pro-drop languages.³ Consider Arabana-Wangkangurru, a

¹Essential definition provided by the Mirriam Webster Online Dictionary at https://www.merriam-webster.com/dictionary/pronoun

²Grammatical and social gender should not be confounded, but are often treated interchangeably by lay audiences.

³First described by Perlmutter (1968), the phenomenon of "pro-drop languages" relates to languages, in which, in certain cases, some classes of pronouns can be omitted (e.g., Italian).

language spoken in Australia, in which a speaker uses different pronouns depending on whether the referent is part of the same social or ritual group (moiety) (Hercus, 1994). As such, pronouns shape how we perceive individuals and can even reflect cultural aspects (e.g., Kashima and Kashima, 1998) and ideologies (e.g., Muqit, 2012). Consequently, pronoun usage should be considered a sensitive aspect of natural language use.

Accordingly, in many western societies, these phenomena have been drawing more and more attention. For instance, in 2020, the American Dialect Society voted "(My) Pronouns" as the 2019 Word of the Year and Singular "They" as the Word of the Decade (Roberts, 2020). Recently, there has been a shift in pronoun usage (Krauthamer, 2021), partially due to shifts in the perception of gender, driven by the queer-feminist discourse (e.g., Butler, 1990, 2004). Related to this is the open discussion of identity beyond binary gender. For instance, a person who does not identify their gender within the gender binary (e.g., a nonbinary or genderqueer person) might use singular "they" as their pronoun. Recently, the French dictionary "Le Robert" added the non-binary pronoun "iel" to its list of words.⁴

This "social push" to respect diverse gender identities also affects NLP. Recent studies have pointed out the harms of the current lack of non-binary representation in data, embeddings, and tasks (Cao and Daumé III, 2021; Dev et al., 2021). However, the research landscape on modern pronoun usage is surprisingly scarce, hindering progress for fair and inclusive NLP. This lacuna is in direct contradiction of the UN's sustainable development goals, 5 which include gender equality (goal 5).

Linguistic research has identified further identity aspects of pronouns, beyond gender (Miltersen, 2016). Specifically, *nounself* pronouns are functionally turning pronouns from a *closed* into an *open* word class. To the best of our knowledge, NLP has completely ignored these aspects so far. We did not find a single work systematically describing all of the currently existing phenomena, even just in English 3rd person pronoun usage (let

In contrast, in "non-pro-drop languages", pronouns cannot be omitted (e.g., German).

alone other languages).⁶ In contrast, many discussions are taking place on queer Wikis and forums. While it is still unclear which of these phenomena will persist over the following decades, people use and discuss them. Accordingly, we as a research community should adapt.

Contributions. 1) We are the first to provide a systematic overview of existing phenomena in English 3rd person pronoun usage. Our results will inform future NLP research on ethical NLP and non-binary representation. We provide the first NLP work acknowledging *otherkin* identities. We support our observations with a corpus analysis on Reddit. 2) Based on our overview, we derive five desiderata for modeling third-person pronouns, which we validate with a survey among 39 individuals (coupled with a pre-study with 149 participants), most of which identify as non-binary. Based on these criteria, 3) we discuss various existing and novel paradigms for when and how to model pronouns in NLP. 4) Finally, we quantify the impact of discrimination-free non-modeling of pronouns on a widely established benchmark.

2 Related Work

While there are some works in NLP on genderinclusion (e.g., Dev et al., 2021) and gender bias in static (e.g., Bolukbasi et al., 2016; Gonen and Goldberg, 2019; Lauscher and Glavaš, 2019; Lauscher et al., 2020, inter alia) and contextualized (e.g., Kurita et al., 2019; Bordia and Bowman, 2019; Lauscher et al., 2021, inter alia) language representations as well as works focusing on specific gender bias in downstream tasks (e.g., Rudinger et al., 2018; Webster et al., 2018; Dev et al., 2020; Barikeri et al., 2021), we are not aware of any work that deals with the broader field of identity-inclusion. Thus, there is no other NLP work that deals with a larger variety of pronouns and acknowledges pronouns as an open word class. For surveys on the general topic of unfair bias in NLP we refer to Blodgett et al. (2020) and Shah et al. (2020). Recently, Dev et al. (2021) pointed at the representational and allocational harms (Barocas et al., 2017) arising from gender-exclusivity in NLP. They surveyed queer individuals and assessed non-binary representations in existing data sets and embeddings. In contrast, we specifically look at third-person pronoun usage and how to model such phenomena. Webster

⁴https://dictionnaire.lerobert.com/dis-moi-robert/raconte-moi-robert/mot-jour/pourquoi-le-robert-a-t-il-integre-le-mot-iel-dans-son-dictionnaire-en-ligne.html

⁵https://sdgs.un.org/goals

⁶For instance, while we found hits for the Google Scholar query "neopronoun", we did not get any results for variants of "nameself pronoun", or "emojiself pronoun".

et al. (2018) provide a balanced co-reference resolution corpus with a focus on the fair distribution of pronouns but only focus on the gendered binary case. Closest to us, Cao and Daumé III (2021) discuss gender inclusion throughout the NLP pipeline beyond binary gender. While they are the first to consider gender-neutral pronouns, including some neopronouns, they do not acknowledge the broader spectrum of identity-related pronoun phenomena.

3 A Note on Identity and Pronouns

This work focuses on the relationship between identity and pronouns. *Identity* refers to an individual's self-conceptualization, relating to the question of what makes each of us unique (Maalouf, 2000). It can be seen as a two-way process between an individual and others (Grandstrand, 1998), and relates to different dimensions, e.g., one's gender.

Gender Identity. Gender identity, as opposed to gender expression or sex, is one's inner sense of gender (Stryker, 2017; Keyes et al., 2021). In this work, we recognize gender identities beyond a cisnormative binary (*cis man, cis woman*), e.g., transgender, non-binary, agender, etc.

Otherkin Identity. Individuals with otherkin identity do not entirely identify as human (Laycock, 2012), e.g., vamp. Miltersen (2016) note that otherkin individuals often identify with *nounself* pronouns matching their kin.

Stryker (2017) highlights the strong relationship between gender identity and pronouns. As Raymond (2016) notes, pronoun choices construct the individual's identity in conversations and the relationship between interlocutors. According to Cao and Daumé III (2021), pronouns are a way of expressing referential gender. Referring to an individual with sets of pronouns they do not identify with, e.g., resulting in misgendering, is considered harmful (e.g., Dev et al., 2021).

4 Phenomena in Third-person Pronoun-Usage

We describe existing phenomena and analyze their presence in a collection of threads from Reddit.⁷

4.1 Existing Phenomena

Overall, individuals can choose n sets of pronouns with $n \geq 0$. If n = 0, the individual does not identify with any singular 3rd person pronoun. If n > 1, the individual identifies with more than



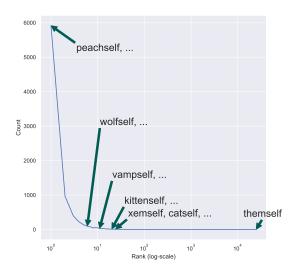


Figure 1: Token ranks (log-scale) and rank counts of the tokens returned against our reflexive regular expression pattern from Reddit with example annotations.

one set of pronouns. Each set is possibly reflecting overlapping or non-overlapping aspects of their identity. We provide examples of these sets in Table 1. Note that this list is non-exhaustive and that the described phenomena are non-exclusive.

Gendered Pronouns. In English, two sets of gendered pronouns are available, *he/him/himself* and *she/her/herself*.

Gender-Neutral Pronouns. Given the history of generic singular *they* in English (e.g., Who was at the door? *They* left a note.), there has been an uptake of singular *they* by non-binary individuals as a gender-neutral pronoun option⁸ (Conrod, 2019; Konnelly and Cowper, 2020). Further, there has been increasing institutional recognition with dictionaries and style guides supporting its use.

Neopronouns. As an alternative to the singular *they*, individuals started creating and sharing novel sets of 3rd person pronouns (McGaughey, 2020). More traditional and rather well-known sets of neopronouns include, e.g., the so-called Spivak pronouns *e/emself* (used in (Spivak, 1990)) and related variations. During our research, we observed various subcategories of neopronouns, only partially described in the academic literature.

Nounself Pronouns. Nounself pronouns are "[...] prototypically transparently derived from a spe-

⁸https://gendercensus.com/results/202 1-worldwide-summary/

cific word, usually a noun" (Miltersen, 2016). Individuals may identify with certain nouns, possibly corresponding to aspects of their identity, e.g., *kitten/kittenself*, *vamp/vampself*. The author notes the difficulty of clearly defining nounself pronouns, neopronouns, and other phenomena. The phenomenon is assumed to have first appeared in 2013.

Emojiself Pronouns. Similar to nounself pronouns, individuals may identify with sets of emojis, possibly reflecting different aspects of their identity, e.g., self. Emojiself pronouns are intended for written communication. Note that, at the time of writing this manuscript, no academic description of emojiself pronouns seems to exist. However, we were able to find evidence of their existence on several social media platforms and wikis, e.g., Tumblr, MOGAI Wiki, Twitter, and Reddit. 12

Numberself Pronouns. Another form of neopronouns/ nounself pronouns are numberself pronouns. Analogous to before, we assume that here, the individual identifies or partially identified with a number, e.g., *0/0/0s/0s/0self*.¹³

Nameself Pronouns. Individuals may identify with pronouns build from their name, e.g., John/Johnself, overlapping with nullpronomials.¹⁴

Alternating Pronouns. Suppose someone identifies with more than one set of pronouns. In that case, the pronouns they identify with can be either equally identified-with sets, or potentially change depending on the context (*mutopronominal*). As such, individuals who are also performers may use *stage pronouns*. Similarly, genderfluid individuals may identify with a certain pronoun at a certain point in time (*pronoun fluidity*, (Cherry-Reid, 2020)). Some individuals identify with the pronouns of the person who is referring to them (*mirrored pronouns*). Others use set(s) of *auxiliary*

pronouns, e.g., for situations when people referring to them have problems with using the most identified-with sets of pronouns (e.g., in the case of emojiself pronouns and oral communication). Alternating pronoun sets may be even used in the same sentence for the same individual.¹⁵

No Pronouns. Some individuals do not identify with any pronouns. In this case, some individuals identify most with their name being used to refer to them, nameself pronouns, or avoid pronouns.

4.2 Corpus Analysis: Neopronouns in Reddit

We conduct an additional analysis for the presence of neopronouns in Reddit. To this end, we use Reddit threads (2010–2021), cleaned by previous work and provided through Huggingface Datasets (127,445,911 lines). The data set includes comment title, text, and subreddit. 16 Since we are interested in capturing novel pronouns, but the list of possible pronouns is indefinite, we proxy neopronouns via the suffixes self and selves to indicate the reflexive case. We match them through a regular expression. Additionally, we filter out non-3rd person pronouns (e.g., yourself, ourselves, plural themselves) as well as common variations of these (e.g., urself) and other common non-pronoun expressions we found in the data (e.g., do-it-yourself). This process leaves us with a total of 9,075 unique tokens with in total 74,768 textual mentions.

Results. Unsurprisingly, an initial manual analysis reveals that many of the matches are false positives, i.e., not real neopronouns like non-self, a common concept in Buddhist philosophy. However, our method still finds relevant cases. Note, that in this work, we do not explicitly deal with false positives - we are merely interested in whether our heuristic helps us to detect some sets of neopronouns at all, thus demonstrating their existence in realworld conversations. Examples of neopronouns we found are depicted in Table 2. Many discussions containing nounself pronouns center on the phenomena themselves, including, e.g., individuals stating that they are interested in using a specific pronoun or that they refuse to acknowledge the phenomenon. Some discussions involve people reporting on personal experiences and problems and seeking advice. To obtain a high-level quantitative

⁹E.g., https://pronoun-archive.tumblr.com /post/188520170831

¹⁰https://mogai.miraheze.org/wiki/Emoj iself; according to the article, the origin of emojiself pronouns is unclear but might date back to 2017

¹¹Example of a user complaining about LinkedIn not allowing for emojiself pronouns in the pronoun field: https://twitter.com/frozenpandaman/status/1412314202119700480/photo/1

¹²E.g., https://www.reddit.com/r/QueerVexi
11ology/comments/p09nek/i_made_a_flag_f
or_the_emojiself_pronoun_set/

https://pronoun-provider.tumblr.com/
post/148452374817/i-think-numbers-as-pro
nouns-would-be-pretty-cool

¹⁴https://pronoun.fandom.com/wiki/Null pronominal

¹⁵https://www.reddit.com/r/NonBinary/c
omments/jasv5r/alternating_pronouns_in_s
ame_sentence/

¹⁶https://huggingface.co/datasets/sent ence-transformers/reddit-title-body

Match	Thread Title	Thread Excerpt
meowself	Fureedom Mewnite can die in my litterbox.	I don't like this game. But I still want meowself to play it, meow. Cause it's fun, even though I hate it.
	Neopronouns are going too far.	I get some pronouns like ze/zir, xe/xem, etc. I agree with those. But why are people using ghost/ghostself and meow/meowself? That's really utter bullshit.
bunself	I am genderfluid, and pansexual. I have a lot of SJW friends. AMA!	They/them pronouns are coolest with me, but I won't be angry if you use he or she. You can use bun/buns/bunself, if you are feeling special. (That's a joke.)
	Xi am so proud to announce that the new word of the year is	-Cinnagender- which means you identify with our beloved and innocent cinnamon buns. The pronoun set is cinne/cinns/cinnself or alternatively bun/buns/bunself i am so happy to be a member of a community that ignores the oppressive gender binary, which is a social construct, i.e., it is not real
zirself	Ran into our first roadblock	I asked what I could do to help zir lowering the feeling of disphoria, and ze said zed maybe feel better about zirself if zed drink a tea.
	If you're a horrible person on- line, you're probably a horrible person offline too.	Hello folks. Omg. I think this individual is about to hurt zirself! (emphasis on "zirself". COMEDIC GENIUS)

Table 2: Example neopronouns and corresponding excerpts from Reddit retrieved via our heuristic method. We slightly modified the excerpts to lower searchability and increase the privacy of the users.

view, we compute the matches' ranks as the number of texts in which particular matches occurred (including false positives) against their number of tokens (e.g., there is only 1 match, which appeared in 24,697 texts; there are 2 matches, which appeared in 198 texts, etc.). We show the results in Figure 1 (log-scale). The result is a highly skewed Zipf's distribution: while the highest ranks appear only once (e.g., *themself* with 24,697 mentions), some tokens appear only a couple of times (e.g., the neopronoun *xemself* with 24 mentions), and the vast majority appears only once (e.g., many nounself pronouns such as *peachself*).

5 How Can and Should We Model Pronouns?

We devise five desiderata based on our observations, personal experiences, expert knowledge from interactions with LGBTQIA+ associates, and informal discussions with individuals using genderneutral pronouns. We validate the desiderata through a survey. Here, we collect opinions from 39 individuals (149 in the pre-study), most of whom identify as non-binary. We then assess how well classic and novel NLP pronoun modeling paradigms fulfill the criteria.

5.1 Desiderata

D1. Refrain from assuming an individual's identity and pronouns. A model should not assume an individual's identity, e.g., gender, or pronouns based on, e.g., statistical cues about an individual's

ual's name, also not in a binary gender setup. Only because the name *John* typically appears together with the pronoun *he*, the model should not assume that a person with the name *John* identifies as a man and that every *John* uses the pronoun *he*.

D2. Allow for the existing sets of pronouns as well as for neopronouns. A model should be able to handle not only the existing set of "standard" pronouns in a language but also other existing pronouns, e.g., neopronouns.

D3. Allow for novel pronouns at any point in time. On top of **D2**, a model should allow for novel, i.e., unseen, pronouns to appear at any point in time. This condition is necessary to account for the fact that neopronouns are not a fixed set, but evolving, and because related phenomena (emojiself and nameself pronouns) turn pronouns from a *closed* to an *open class* part of speech.

D4. Allow for multiple, alternating, and changing pronouns. A model should not assume that the pronoun set for an individuum at time t will be the same as at time t-1. Even within the same sequence, pronoun sets might change.

D5. Provide an option for individuals to define their sets of pronouns. While most NLP models are trained offline and do not interact with the user, some are designed to interact with individuals, e.g., dialog systems. Here, letting individuals provide their sets of pronouns can help avoid harmful interactions (depending on the sociotechnical scenario).

5.2 Validation

Survey Design. We divide the survey into three parts: first, participants are asked for demographic information (age, (gender) identity, native language(s), pronouns). The second part asks for their opinion on D1–D5. We first provide a general contextualization of our research and describe the task. Participants are asked to indicate how much they agree with each desideratum (ordinal scale, 1 (I don't agree) to 5 (I absolutely agree)). We also allow for leaving additional comments. The third part relates to a case study on machine translation. We inform the participants that their participation is completely voluntary and that they will not receive any compensation. All questions are optional. To avoid sequence effects, we create multiple versions of the survey shuffling the order of the desiderata. We obtained ethical approval for the design by one of our universities' institutional review board.

Survey Distribution. Opting to collect opinions from affected individuals, we distribute the survey through various international LGBTQIA+ networks, e.g., QueerInAI, ¹⁷ Committee on LGBTQ+ [Z] Issues in Linguistics, ¹⁸ as well as through local LGBTQIA+ groups, e.g., Transgender Network Switzerland. ¹⁹ In an initial pre-study, which was open for participation between 22nd of March and 4th of May 2022, we validated our design. In total, 149 individuals participated in this phase (more than 8x more than in (Dev et al., 2021)). ²⁰ The main phase of the survey was open for participation between 18th of June and 1st of August 2022.

Partcipant Statistics. In total, 44 individuals participated in the main phase of our survey, more than in any other survey on (gender) identity and language technology we are aware of. Participant ages range from 14 to 43 (the majority between 20 and 30). For the rest of the analysis, we removed all records from individuals under the age of 18. These individuals indicated that they speak diverse native languages (e.g., German, English, Danish, Persian, Russian). Participants provided between 0 and 4 identity terms (e.g., genderfluid, genderqueer, trans*masculine, etc.), with the majority identify-



¹⁸https://www.linguisticsociety.org/co
ntent/committee-lgbtq-z-issues-linguisti
cs-cozil

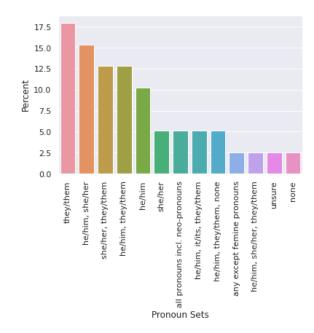


Figure 2: Distribution over English pronoun sets the participants of our survey identify with. We apply slight lexical normalization to the pronoun strings provided in the free text field (e.g., $he \rightarrow he/him$, etc.).

Score	1	2	3	4	5	Avg
D1	5.13%	2.56%	0.00%	33.33%	58.97%	4.38
D2	2.56%	0.00%	5.13%	17.95%	74.36%	4.62
D3	2.56%	0.00%	12.82%	25.64%	58.97%	4.38
D4	2.56%	5.13%	2.56%	23.08%	66.67%	4.46
D5	0.00%	2.56%	5.13%	20.51%	71.79%	4.62

Table 3: Agreement distribution for our desiderata D1–D5. We report the % agreement per score (1=*I don't agree*, 5=*I absolutely agree*) as well as the average score.

ing as non-binary. Thus, we believe our results to reflect cultural and (gender) identity diversity. Figure 2 shows the distribution over the English pronoun sets participants identify with.

Agreement with the Desiderata. We show the distribution of agreement scores for each desideratum in Table 3. Overall, we note high agreement (on average 4.38–4.62). Thus, we conclude our proposed desiderata to provide valuable orientation for the treatment of pronouns leading to more identity-inclusive language technology.

5.3 Modeling Paradigms

We compare four general modeling paradigms with the desiderata D1–D5 in Table 4.

Classic Statistical Modeling. Traditionally, pronouns have been treated as a *closed word class*. Generally, statistical models do not make as-

¹⁹https://www.tgns.ch

²⁰All trends observed in the pre-study were confirmed in the main phase of the survey.

Paradigm	D1	D2	D3	D4	D5	
Classic	X	Х	X	Х	Х	
Bucketing	X	✓	✓	?	X	
Delexicalization	✓	✓	✓	✓	X	
Post-hoc	1	1	1	1	1	

Table 4: Modeling paradigms and how they allow for fullfilling the desiderata D1–D5.

	Train	Dev	Test	Total
PRP PRP\$	64,476 14,535	7,881 1,783	8,067 1,935	80,424 18,253
Total	79,011	9,664	10,002	98,677

Table 5: Number of pronoun replacements in the training, development, and test portion of OntoNotes 5.0 for PRP and PRP\$, respectively.

sumptions about this (except if the vocabulary is manually curated). However, in models exploiting co-occurrences, e.g., via word embeddings (GloVe (Pennington et al., 2014)) or deep language models (BERT (Devlin et al., 2019)), the models will likely misrepresent underrepresented pronounrelated phenomena. Dev et al. (2021) provided an initial insight by showing that singular *they* and the neopronouns *xe* and *ze* do not have meaningful vectors in GloVe and BERT.

Bucketing. One option, previously discussed by Dev et al. (2021), is to apply bucketing, i.e., to decide on a fixed number of majority classes, e.g., *male* pronouns, *female* pronouns, and one or multiple classes for the "rest of the pronouns", e.g., *other*. The advantage of this approach is that it can map existing and novel pronouns to the *other* class. However, it still makes identity assumptions – and due to unequal representations of *main* and *other* classes, it will inevitably lead to discrimination.

No Modeling – Delexicalization. Given that the classic approach and bucketing both lead to unfair treatment of underrepresented groups, the alternative is to explicitly not model pronouns in their surface forms. This process, commonly named delexicalization, has proved helpful for other tasks where models capture misleading lexical information, e.g., fact verification (e.g., Suntwal et al., 2019), or resource-lean scenarios, e.g., cross-lingual parsing (e.g., McDonald et al., 2011).²¹ In this case, the model is forced to not rely on spurious lexical cues related to gender, e.g., that *John* occurs most often

with the pronoun *he*. Instead, the model learns a single representation for all pronouns and relies on other task-related conceptual and commonsense information for disambiguation.

Post-hoc Injection of Modeling Information/ Modeling at Test Time. For human-to-human interactions, several LGBTQIA+ guides recommend to (1) first try generic pronouns (e.g., singular they), and (2) switch to other sets of pronouns once the conversation partner communicates them. For uncommon or novel pronouns, several web pages have explicitly been set up for practicing how to use them.²² In this work, we propose that NLP systems should work similarly – if technically possible and depending on the concrete sociotechnical deployment scenario. To this end, we can use intermediate training procedures (e.g., Hung et al., 2021) for pronoun-related model refinement. E.g., we can use synthetic data created through similar procedures as the ones employed on these websites. Another option is only model pronouns at test time, e.g., through simple replacement procedures.

6 The Effect of Delexicalization

In §5.3, we discussed delexicalization, i.e., not modeling lexical forms of pronouns, as one way to counter exclusion in statistical modeling and bucketing. A possible counter-argument against this approach is that omitting the surface forms will lead to poor performance on pronoun-related tasks. We experimentally quantify the loss from (fairer) delexicalization in co-reference resolution.

6.1 Experimental Setup

Task, Dataset, and Measures. We resort to coreference resolution, a task where knowledge about pronouns and related gender assumptions play an essential role. We use the English portion of *OntoNotes 5.0* (Weischedel et al., 2012), which consists of texts annotated across five domains (news, conversational telephone speech, weblogs, USENET newsgroups, broadcast, and talk shows). We prepare three variants: (i) the original data; (ii) we *replace all pronouns* in the test set with the respective part-of-speech token, according to the Penn Treebank Project (Santorini, 1990), i.e., PRP for personal pronouns, and PRP\$ for possessive pronouns. Finally, we provide a version (iii) where we replace pronouns in all splits. Note that our

²¹In fact, accounting for novel pronouns and novel ways of using pronouns is a resource-lean scenario.

 $^{^{22}}$ E.g., https://www.practicewithpronouns.com/#/?_k=66emp7

	MUC		$CEAF_{\phi 4}$			\mathbf{B}^3			AVG			
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
(Dobrovolskii, 2021)	84.9	87.9	86.3	76.1	77.1	76.6	77.4	82.6	79.9	_	-	81.0
reproductionreplace test set	84.7 69.7	87.5 70.7	86.1 70.2	75.6 63.2	76.7 49.1	76.1 55.2	77.2 50.1	82.0 56.1	79.5 52.9	79.2 61.0	82.1 58.6	80.6 59.4
$\Delta_{repl.test-repr.}$	-15.0	-16.8	-15.9	-12.4	-27.6	-20.9	-27.1	-25.9	-26.6	-18.2	-23.5	-21.2
 replace all 	81.6	83.1	82.4	73.08	72.9	73.0	72.3	75.3	73.7	75.7	77.1	76.4
$\Delta_{repl.all-repr}$.	-3.1	-4.4	-3.7	-2.5	-3.8	-3.1	-4.9	-6.7	-5.8	-3.5	-5.0	-4.2

Table 6: Results of the delexicalization experiment. We report the results of the RoBERTa large-based word-level co-reference resolution model from Dobrovolskii (2021), our reproduction, and variants trained or tested on versions of the data set in which we replace the pronouns. All scores were produced using the official CoNLL-2012 scorer. We report precision (P), recall (R), and F1-score (F1) for MUC, CEAF $_{\phi4}$, and B³, respectively, as well as the averages (AVG). The rows highlighted in gray indicate the obtained losses.

strategy is pessimistic as we also replace non-3rd person pronouns, i.e., I, you, etc. We show the number of replacements in Table 5. For scoring, we use the official CoNLL-2012 scorer (Pradhan et al., 2012). We report the results in terms of MUC (Vilain et al., 1995), B^3 (Bagga and Baldwin, 1998), and $CEAF_{\phi 4}$ (Luo, 2005) precision, recall, and F1-measure, and the averages across these scores.

Models and Baselines. We want to obtain an intuition about the tradeoffs in the delexicalization setup, not to outperform previous results. For this reason, we resort to the recently proposed wordlevel co-reference model (Dobrovolskii, 2021), a highly efficient model competitive with the stateof-the-art. The model consists of a separate coreference resolution module and a separate span extraction module. In an initial step, we compute token representations from a Transformer (Vaswani et al., 2017)-based encoder through the aggregation of initial representations via learnable weights. Next, we compute co-reference relationships. We pass the token representations into an antecedentpruning procedure based on a bilinear scoring function. This way, we obtain k antecedent candidates for each token through coarse-grained scoring. An additional feed-forward neural network computes finer-grained scores. The final antecedent score is the sum of those two scores. Finally, we select the candidate with the highest score as the antecedent. Negative scores indicate no antecedent. Tokens assumed to be part of a co-reference relationship are passed into the span extraction module. The module consists of an additional feed-forward network, followed by convolutions with two output channels (for start and end scores). For further details, see the original work. Our baseline is the model trained and evaluated on the original OntoNotes portions

(reproduction). We compare with the evaluation of this model on the pronoun-replaced test set (replace test set) and a version of this model trained on the replaced training set and evaluated on the replaced test set, respectively (replace all).

Model Configuration, Training, and Optimization. We choose RoBERTa large (Liu et al., 2019)²³ as the base encoder and fix all other hyperparameters to the ones provided in the original implementation of Dobrovolskii (2021): the window size is set to 512 tokens, dropout rate to 0.3, the learning rate of the encoder is set to $1 \cdot 10^{-5}$ and of the task-specific layers to $3 \cdot 10^{-4}$, respectively. We train the co-reference module with a combination of the negative log marginal likelihood and binary cross-entropy as an additional regularization factor (weight set to 0.5). The span extraction module is trained using cross-entropy loss. We optimize the sum of the two losses jointly with Adam (Kingma and Ba, 2015) for 20 epochs and apply early stopping based on validation set performance (word-level F1) with a patience of 3 epochs.

6.2 Results and Discussion

We show the results in Table 6. We are roughly able to reproduce the results reported by (Dobrovolskii, 2021), confirming the effectiveness of their approach and the validity of our setup. When we replace pronouns in the test set, the results drop massively, with up to -27.6 percentage points CEAF $_{\phi4}$ recall. This decrease demonstrates the heavy reliance of this model on the lexical surface forms of the pronoun sets seen in the training. However, when we replace the pronouns in the training portion of OntoNotes with the special tokens, we can mitigate these losses by a large margin (losses up

²³https://huggingface.co/roberta-large

to $-5.8~\mathrm{B}^3~\mathrm{F1}$, and on average $-4.2~\mathrm{F1}$). These results are highly encouraging, given that a) we replaced *all* pronouns, including non-third person pronouns, and b) the model has not been trained on these placeholders in the pretraining phase. The model can not rely on possibly discriminating correlations between names or occupations and pronoun sets. It therefore represents neopronouns the same way as established pronoun sets. A delexicalization approach can increase fairness in co-reference resolution and retain high system performance. We can expect even smaller drops from a more careful selection of replacements, and, possibly, from intermediate training procedures that strengthen the representation of the placeholder tokens.

7 Conclusion

This work provides an initial overview of the plethora of current phenomena in 3rd person pronoun usage in the English language. For practical and ethical reasons, the NLP community should acknowledge the broad spectrum of possible identities and the respective manifestations in written and oral communication. Language is consistently evolving, and NLP researchers and practitioners should account for this to provide genuinely inclusive systems. Notably, pronouns, traditionally handled as a closed class of words, seem to function closer to an open class. Based on the observations from our literature search, research in non-academic, publicly-available writing, a corpus study, and a survey, we defined five desiderata. We validated those and applied them to the discussion of existing and novel modeling paradigms. Our findings raise the questions when and how to model pronouns and whether and how to include users in these decisions. With this work, we hope to start a broader discussion on the topic. Our study can inform future NLP research and serve as a starting point for creating novel modeling procedures. All code needed to reproduce our experiments is publicly available at https: //github.com/anlausch/pronouns.

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Further Ethical Discussion

We have described phenomena related to third-person pronouns focusing exclusively on the English language. Naturally, this work comes with several limitations. For instance, while we pointed the reader to the variety of pronoun-related phenomena in other languages, a thorough *multilingual and cross-lingual discussion* would have exceeded the scope of this manuscript. This lacuna includes the discussion of neopronouns in other languages. Similarly, while we acknowledge identities beyond binary gender and otherkin identities, due to our focus on pronouns, we did not investigate *other identity-related terms*. This aspect includes their handling in language technology and the range of issues related to identity-exclusivity.

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