

# Natural Language Processing for Dialects of a Language: A Survey

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State-of-the-art natural language processing (NLP) models are trained on massive training corpora, and report a superlative performance on evaluation datasets. This survey delves into an important attribute of these datasets: the dialect of a language. Motivated by the performance degradation of NLP models for dialectic datasets and its implications for the equity of language technologies, we survey past research in NLP for dialects in terms of datasets, and approaches. We describe a wide range of NLP tasks in terms of two categories: natural language understanding (NLU) (for tasks such as dialect classification, sentiment analysis, parsing, and NLU benchmarks) and natural language generation (NLG) (for summarisation, machine translation, and dialogue systems). The survey is also broad in its coverage of languages which include English, Arabic, German among others. We observe that past work in NLP concerning dialects goes deeper than mere dialect classification, and . This includes early approaches that used sentence transduction that lead to the recent approaches that integrate hypernetworks into LoRA. We expect that this survey will be useful to NLP researchers interested in building equitable language technologies by rethinking LLM benchmarks and model architectures.

CCS Concepts: • **Computing methodologies** → **Natural language processing**.

Additional Key Words and Phrases: NLP, dialects, natural language processing, linguistic diversity, large language models, inclusion

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## 1 INTRODUCTION

Natural language processing (NLP) is an area of artificial intelligence that deals with the processing of text. NLP tasks are broadly viewed as two categories: natural language understanding (NLU) and natural language generation (NLG). The former covers tasks such as sentiment analysis, where the

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input is a textual sequence, but the output is a label or a set of labels. The latter includes tasks such as summarisation, where both the input and the output are textual sequences. The state-of-the-art in NLP, for both NLU and NLG, is based on Transformer-based models. Large language models (LLMs) that use decoders in the Transformer architecture have significantly increased attention toward NLP from several domains, including but not limited to science, engineering, and technology. LLMs released by commercial organisations report an increasingly higher number of parameters and, resultantly, improved performances on several NLP tasks on benchmark datasets centered around tasks. NLP approaches using LLMs are largely viewed as black-box models trained on massive corpora whose composition is not accurately known. This survey dissects one of many attributes in which variations may exist in the training and test corpora: dialects of a language. Therefore, this survey presents NLP techniques for dialects of a language.

A dialect is defined as the regionally or locally based varieties of a language [Haugen 1966]. In general, a dialect combines the structure and vocabulary of two or more languages, similar to Creole languages<sup>12</sup> or are referred to as national variants of a language. A unique example is Australian English which itself derives its phonemes from Southern British English [Cox 2006; Cox and Palethorpe 2007] but has also developed its own unique vocabulary [Moore 1999]. In this paper, we use the word ‘dialect’ interchangeably with ‘national/cultural variants’ of a language while acknowledging implications including the perpetuation of social hierarchies. The focus of this survey is the adaptation and evaluation of NLP tasks and approaches on dialects of a language.

In general, our survey is catalysed by the recent efforts in extending LLMs on NLP tasks for dialects of different languages. As researchers continue to look ‘under the hood’ of LLMs, we believe that dialectic differences in training and testing datasets will become increasingly scrutinised, and models will be enhanced to become robust to dialects. As a result, we hope that this survey will help readers and researchers understand past work in NLP techniques for dialects of a language, and contribute to ideas about fair and equitable NLP in the future. Our survey covers a broad range of approaches from classical NLP as well as modern NLP where pre-trained language models (PTLMs) are leveraged.

There have been surveys in the past in overlapping areas. [Zampieri et al. 2020] is a survey of NLP for dialects spanning languages from around the world. The paper describes in detail the available corpora, and then summarises past approaches to fundamental NLP problems such as POS tagging and parsing, along with applications to NLP. Our survey builds upon theirs in three ways. Firstly, we cover a wider range of downstream tasks, namely summarisation, sentiment analysis and so on. Also, this survey contains recent papers, which highlight increasingly growing attention towards NLP for dialects. Finally, the exposition of our survey follows a deep learning-centric view: we divide past work into NLU and NLG. Another survey by [Blodgett et al. 2020] describes biases of different kinds in an analysis of language technologies, including dialectic bias. We derive from their survey to formulate the motivation and trends in NLP for dialects. Finally, extensive surveys focussing on languages from the Middle East have been reported [Darwish et al. 2021; Shoufan and Alameri 2015]. These are surveys of NLP for standard and dialectic Arabic, primarily focusing on dialect identification and synthesis in the form of machine translation. Our survey unifies the efforts in dialects of languages belonging to multiple language families. The contribution of our survey is:

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<sup>1</sup>A Creole language, or simply creole, is a stable natural language that develops from the process of different languages simplifying and mixing into a new form (often, a pidgin), and then that form expanding and elaborating into a full-fledged language with native speakers, all within a fairly brief period.

<sup>2</sup> [Lent et al. 2023] is a recent work that highlights social and scholarly stigmatisation of Creole languages that has resulted in limited advances in NLP for these languages. We also acknowledge the association between perceived social hierarchies and dialects of a language [Kroch 1986]

- We present past work in terms of NLU and NLG tasks.
- We highlight trends and future directions, and provide summary tables that will help researchers interested in dialectic NLP research.
- The survey covers a broad range of languages from around the world.
- The survey connects past research with cutting-edge research using state-of-the-art models.

The rest of the paper is organised as follows. We motivate the need for a discussion on dialects in Section 2. We define the scope of the paper and highlight key trends in Section 3. We then cover dialect-specific resources in Section 4. Following that, Section 5 covers several NLU tasks: dialect identification, sentiment analysis, parsing, and NLU benchmarks. Section 6 presents relevant approaches in NLG for machine translation, summarisation and so on. Finally, we conclude the survey and discuss future work in the context of NLP research as well as social/ethical implications in Section 7. The survey contains several summary tables that will be useful for future research in the area.

## 2 MOTIVATION

We now motivate the need for this survey via four aspects. We first describe a set of linguistic studies that study dialectic variations to highlight the relevant NLP challenges. We then show why a deeper analysis in dialects is important to better benchmark LLMs, and NLP techniques and how it has ramifications for the responsible and equitable development of technologies. Finally, recent papers focusing on the dialect-robust development of NLP techniques indicate an emerging trend in NLP research. The four aspects highlight that the survey will provide pointers to the future of linguistic and cultural inclusion in NLP.

### 2.1 Linguistic Challenges Posed by Dialects

Linguistic researchers have studied the characteristics of non-native users of a language. [Nagata 2014] study the influence of native language on a person’s usage of English. With the help of native speakers of Asian languages, they show that the probability of native language influence is invariant with English language proficiency. [Lee and Jun 2016] analyse four dialects of English (British, Indian, Philippines, and American) and show linguistic variations between them. They particularly highlight different preferences for modals among the four dialects. [Haugh and Bousfield 2012] describe the difference between Australian and English data stating: “The focus of jocular mockery and abuse about the job or profession of the target involved their (attested) lack of ability or skill in his chosen area or profession.”. This holds true in several other cultures [Haugh and Chang 2015] including Chinese [Qiu et al. 2021], Indian [Kachru 1965] and Persian [Izadi 2015].

Dialectic differences primarily occur in terms of syntax and vocabulary. Some examples of dialectic differences in English are: ‘I might could help you with that’ in Australian English [Coats 2022], ‘Inside tent can not see leh !’ in Singaporean English [Wang et al. 2017]. or the arbitrary placement of adverbs in native speakers of Asian languages as in ‘Already, I have done it.’ [Nagata 2014]. Also, consider the case of the Samvedi<sup>3</sup> dialect of Marathi, one of 42<sup>4</sup>, where the Samvedi version of the modern standard Marathi sentence “(Transliteration) Mazha naav Pushpak ahe”(Literal: My name Pushpak is) (Translation: My name is Pushpak) is “(Transliteration) Maa naav Pushpak hai”(Literal: My name Pushpak is) (Translation: My name is Pushpak). Samvedi does not exhibit word order differences compared to standard Marathi, but it involves heavy pronunciation relaxation (ahe -> ha, and mazha->maa, in the example above) and the usage of older words.

<sup>3</sup>Samvedi is also called Kadodi and is primarily spoken by the Samvedi Brahmins and Catholics predominantly residing in Vasai City, Maharashtra, India

<sup>4</sup>[https://en.wikipedia.org/wiki/Marathi\\_language#Dialects](https://en.wikipedia.org/wiki/Marathi_language#Dialects)

Another challenge in handling dialects is that two dialects of the same language can be completely mutually unintelligible, and is often correlated with the distance between regions in which that dialect is primarily spoken. A classic example of this is in the case of the Aomori<sup>5</sup> and Okinawan<sup>6</sup> dialects of Japanese which has a total of 47<sup>7</sup> known dialects. Therefore, it is not enough to collect data for one dialect and assume that it will help in NLP for another dialect which indicates that special attention will need to be paid to each dialect to ensure that it will be well-represented.

Dialects assume further importance when people from different cultural backgrounds interact with each other. [Meyer 2014] discusses interactions between people of different cultural backgrounds. The book compares interactions of Australians with people from other cultures in terms of (a) building trust with colleagues, (b) leading teams of a culturally dissimilar background *etc.* An example in the book states that an Australian may invest in shorter small talk than a Mexican with a colleague. [Wang et al. 2022] show that monophthongal vowels spoken by Australian English speakers may be difficult to be understood by Mandarin English listeners.

Further challenges are posed by differences in pragmatics, with influences derived from macro-social factors such as region, social class, ethnicity, gender, age [Haugh and Schneider 2012]. For example, [Schneider 2012] observes differences in small talk across inner circle varieties of English which is also linked to age and gender. [Merrison et al. 2012] showed that in student requests to university staff, there were differences in the way obligation was expressed, and that these differences were linked to different ways of claiming social standing.

Finally, it is important to acknowledge that a large proportion of users of English are L2 speakers, are using English not as a second language in everyday life but have acquired English in school, and use it as a tool for communication when required, *e.g.*, in business settings or on holiday. Research in inter-language pragmatics (see summary [Kecskés 2022] has also shown that there are systematic differences in how L2 learners differ use pragmatic strategies, and how different factors such as length of exposure, study abroad, proficiency) influence these strategies.

Noting the differences in the pragmatic strategies of different dialect speakers provide an important social perspective on dialectal variation. However, these are currently not sufficiently accounted for in NLP.

## 2.2 Rethinking LLM benchmarks

Taking the example of English, there are more English language speakers in countries such as India than the United States, Australia and England [Dunn 2019]. In addition, an even larger number of speakers have acquired English in a classroom context (*e.g.*, in countries such as China, Germany or Russia) and use it mainly as a contact language for specific transactional purposes, *e.g.*, business or education. This latter perspective has been described through the notion of English as a lingua franca as “the common language of choice [...] among speakers who come from different linguistic-cultural backgrounds” [Jenkins 2009]. As [Seidlhofer 2005] points out, “English is being shaped at least as much by its non-native speakers as by its native speakers”.

Yet, the corpora used to train language models and more importantly, the datasets used to evaluate them do not necessarily reflect this gap. In the case of GPT-4, the evaluation dataset consists of questions from the MMLU benchmark written in Standard American English<sup>8</sup>. Standard benchmarks used to claim performance of a language model for English primarily contain Standard American English. It has been found that the performance does not extend to NLU tasks for dialects

<sup>5</sup>[https://en.wikipedia.org/wiki/Tsugaru\\_dialect](https://en.wikipedia.org/wiki/Tsugaru_dialect)

<sup>6</sup>[https://en.wikipedia.org/wiki/Okinawan\\_Japanese](https://en.wikipedia.org/wiki/Okinawan_Japanese)

<sup>7</sup>[https://en.wikipedia.org/wiki/Japanese\\_dialects](https://en.wikipedia.org/wiki/Japanese_dialects)

<sup>8</sup>GPT-4 also claims multilingual performance in various languages using translations of English questions into target languages. Using translations of sentences to claim multilingual ability is inaccurate [Joshi et al. 2023]

of English [Ziems et al. 2022]. This holds for most foundation models that are trained on large amounts of data. The distribution of languages in the training corpora is either not known or difficult to determine. There are variants of English, *i.e.*, dialects, that these models brush under the carpet, despite the existence of corpora of regional varieties of English<sup>9</sup> and of corpora of English as a lingua franca<sup>10</sup>. Some examples showing the impact of dialects on the performance of NLP tasks are presented in Table 1. We note that these papers are from the past few years, which have otherwise witnessed a great development in the reported performance of NLP models.

### 2.3 Fair and equitable technologies

In a multicultural society, people use different dialects. NLP systems that are deployed to serve such multicultural communities must be mindful of the variations between different dialects. Evaluation and mitigation of disparity become an overgrowing need in times when language models claim excellent language performance using datasets from a specific dialect alone. This holds particular importance in terms of the fairness of NLP approaches.

The following papers show the implications of dialects along sociological factors:

- (1) **Performance of NLP models and per-capita GDP:** A recent work by [Kantharuban et al. 2023] show the dialectic gap in performance of LLM-based solutions for machine translation and automatic speech recognition for several dialects including those of Arabic, Mandarin, Finnish, German, Bengali, Tagalog and Portuguese. This shows that the problem is not focussed on a specific region but on languages of the world. The paper also analyses confounding social factors and the associated impact on the size of digitized corpora. They show a positive correlation between gross domestic product per capita and the efficacy of dialectic machine translation.
- (2) **Healthcare monitoring:** [Jurgens et al. 2017] show that there exists a disparity between popular dialect speakers and others in the case of healthcare monitoring<sup>11</sup>.
- (3) **Racial biases in hate speech detection:** [Okpala et al. 2022] show that hate speech classifiers may lean towards predicting a text as true if it uses African-American English.

NLP may not perform as well for dialects of a language, particularly spoken by historically marginalized communities such as the African-American community. This has been shown for language identification where dialects are not predicted as the language since they differ from the standard version of the language [Blodgett et al. 2016].

An idea closely related to the survey is the ‘Bender rule’ in NLP research. The Bender rule states that the language of datasets used for evaluation must be stated explicitly without assuming English to be the implicit default [Ducel et al. 2022]. We similarly believe that languages are not monoliths and dialectic differences must be clearly stated.

### 2.4 Recent work

One observes a renewed interest in using dialects to inform NLP tasks, as shown in Figure 1. The figure was generated using the ACL anthology (<https://aclanthology.org/info/development/>; Accessed on 9th January, 2024.). For “dialects”, we use ‘dialect’, ‘national variet’ (subword for inflections of ‘variety’), ‘national variation’, ‘creole’. For “socio-cultural”, we use the words “cultural”, and “socio-cultural”. We restrict to the year range 2000-2023. [Hovy and Yang 2021] shows that incorporating dialectic aspects is closely related to social factors of language. As a result, incorporating an understanding of dialects of a dataset is pivoting for fairer NLP tools.

<sup>9</sup><https://www.ice-corpora.uzh.ch/en.html>; Accessed on 9th January, 2024.

<sup>10</sup><https://www.kielipankki.fi/corpora/elifa/>; Accessed on 9th January, 2024.

<sup>11</sup>They also propose a method to mitigate the disparity.

NLP Task	Paper	Impact
Language classification	[Blodgett et al. 2016]	Language detection shows lower performance for African-American English.
Sentiment classification	[Okpala et al. 2022]	Text in African-American English may be predicted higher as hate speech.
Natural Language Understanding	[Ziems et al. 2022]	Popular models perform worse on GLUE tasks for African-American English text.
Summarisation	[Keswani and Celis 2021]	Generated multi-document summaries may be biased towards majority dialect.
Machine translation	[Kantharuban et al. 2023]	Significant drop in MT from and to dialects of Portuguese/Bengali/etc. to and from English.
Parsing	[Scannell 2020]	Lower performance of parsers on Mancks Gaellic as compared to Irish/Scottish Gaellic.

Table 1. Examples of adverse impact on NLP task performance due to dialectic variations.

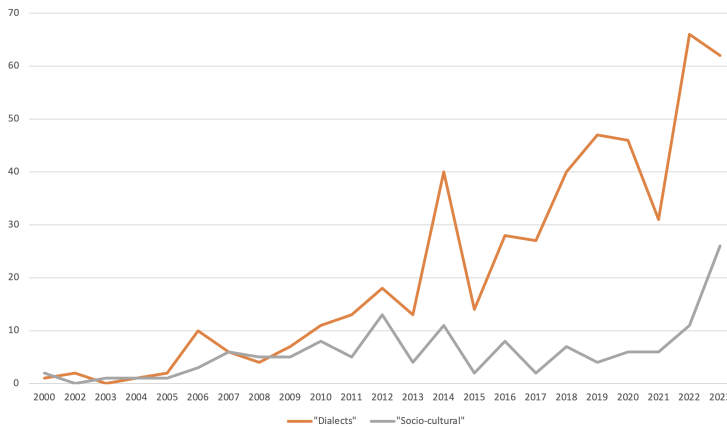


Fig. 1. Number of relevant 'papers-per-year' for keywords 'dialects' and 'socio-cultural' in the ACL Anthology.

Dialect awareness has been shown to improve the performance of NLP tasks such as machine translation [Sun et al. 2023], speech recognition [Plüss et al. 2023]. Recent works have also focused on dialect-aware NLP tasks as in the case of machine translation of dialect to standard language translation as in the case of Chinese [Lu et al. 2022] (for Hokkein, a dialect of Chinese).

### 3 SCOPE & TRENDS

The focus of this survey is NLP approaches that are aware of dialects: either in the form of the choice of the dataset, incorporation in the model or evaluation along dimensions involving dialect. The survey provides a broad introduction to past NLP research on dialects spoken in different parts of the world. In the forthcoming subsections, we clarify the scope of this paper (Section 3.1) and highlight key trends (Section 3.2) that are described in detail in the following sections.

### 3.1 Scope

We select papers that mention the dialect as an attribute of interest. The focus on dialects is either based on the evaluation datasets or the model innovations to improve performance on dialect-specific datasets.

We keep the following out of scope, primarily to effectively manage the scope of the paper:

- (1) **Code-mixing:** Code-mixing involves the use of words from two or more languages, often to reduce cognitive load. While code-mixing focuses on vocabulary, dialects are a combination of syntax and vocabulary.
- (2) **Implicit selection biases:** We also acknowledge that selection biases in datasets may introduce dialectic variations. For example, a dataset of tweets downloaded from a specific country is likely to have predominant dialects spoken in the country. However, we cannot locate these papers in particular, or, for social implications, claim that they are based on dialectic variations of a language without the authors mentioning so.
- (3) **Accent variations:** Finally, we focus on ‘text’-based research while acknowledging that the speech processing community has a rich history of using acoustic data centered around accent. This distinction between dialect and accent has been acknowledged in [Haugen 1966]. The focus on dialects allows us to restrict to the textual form of language which is the typical purview of NLP.
- (4) **Systematic review:** This survey is not a systematic review. We select key representative papers based on our interpretation of the innovation. We acknowledge that we may have missed out on important papers in the field. We will incorporate these papers as communicated by readers/reviewers. However, we cover a broad range of approaches in the survey.
- (5) **Linguistic studies:** While we acknowledge similar rich linguistic work in terms of understanding dialects, we focus on NLP tasks<sup>12</sup>. For example, dialectometry is a research area that studies variations in dialects of a language [Goebel 1993] but is not included in the survey.

### 3.2 Trends

Table 2 summarises the papers covered in this survey. We identify three trends in the past work:

- (1) **Tasks in focus:** Older research dealt with dialectic datasets primarily for dialect classification. Past work shows performance degradation when the text contains dialects of a language as compared to the predominant (*i.e.*, standard) form.
- (2) **Languages in focus:** The papers reporting work on dialects of Arabic are significantly higher than those for dialects of other languages. This has also been accelerated by research forums focussing on Arabic NLP. While the work in English is predominantly for African-American dialect of English, recent papers examine other dialects such as Indian English, Singaporean English and so on.
- (3) **Mitigation is more than perturbation:** Modifying a sentence or its representation to or from its dialectic variations has been achieved by perturbation techniques of varying complexity. However, recent papers show that dialect mitigation can be integrated into the model architecture itself using adversarial networks [Ball-Burack et al. 2021], hypernetworks [Xiao et al. 2023], etc.

It may seem that NLP for dialects of a language only pertains to datasets, *i.e.*, it does not need any specialised handling beyond the introduction of a new dataset. However, we observe that the adaptation of NLP techniques for dialects operates at several points in a typical NLP pipeline:

<sup>12</sup>We cover dialect classification in the section on natural language understanding.

	Languages					Innovation			Problem/Area								
	English	Chinese	Arabic	German	Indic Languages	Other	Dataset	Method/Model	Evaluation/Metric	Benchmark	Dialect Classification	Sentiment Analysis	Machine Translation	Morphology/Parsing	Conversational AI	Summarisation	Speech/Visual
[Nerbonne and Heeringa 1997]	✓																
[Chiang et al. 2006]	✓																
[Habash and Rambow 2006]		✓															
[Chitturi and Hansen 2008]	✓																
[Paul et al. 2011]	✓																
[Lui and Cook 2013]	✓																
[Abdul-Mageed and Diab 2014]	✓																
[Cotterell and Callison-Burch 2014]	✓																
[Darwish et al. 2014]	✓																
[Doğruöz and Nakov 2014]	✓																
[Estival et al. 2014]	✓																
[Jeblee et al. 2014]	✓																✓
[Zampieri et al. 2014]	✓																
[Jørgensen et al. 2015]	✓																
[Xu et al. 2015]	✓																
[Zampieri et al. 2015]	✓																
[Ali and Habash 2016]	✓																
[Blodgett et al. 2016]	✓																
[Burghardt et al. 2016]	✓																
[Goutte et al. 2016]	✓																
[Malmasi et al. 2016]	✓																
[Azouaou and Guellil 2017]	✓																
[Bowers et al. 2017]	✓																
[Crisuolo and Aluisio 2017]	✓																
[Hassan et al. 2017]	✓																
[Jurgens et al. 2017]	✓																
[Mdahaffar et al. 2017]	✓																
[Simaki et al. 2017]	✓																
[Abdul-Mageed et al. 2018]	✓																
[Assiri et al. 2018]	✓																
[Blodgett et al. 2018]	✓																
[Darwish et al. 2018]	✓																
[Elmadany et al. 2018b]	✓																
[Elmadany et al. 2018a]	✓																✓
[Baly et al. 2019]	✓																
[Fadhil et al. 2019]	✓																
[Joukhar et al. 2019]	✓																
[Mulki et al. 2019]	✓																
[Sap et al. 2019]	✓																
[Zampieri et al. 2019]	✓																
[Ahmed and Hussein 2020]	✓																
[Al-Ghadhban and Al-Twairesh 2020]	✓																
[Alshareef and Siddiqui 2020]	✓																
[Demszky et al. 2020]	✓																
[Dunn and Adams 2020]	✓																
[Hanani and Naser 2020]	✓																
[Hou and Huang 2020]	✓																
[Mozafari et al. 2020]	✓																
[Zhao et al. 2020]	✓																
[Ball-Burack et al. 2021]	✓																
[Ben Elhaj Mabrouk et al. 2021]	✓																
[Boujou et al. 2021]	✓																
[El Mekki et al. 2021]	✓																
[Guellil et al. 2021]	✓																
[Keswani and Celis 2021]	✓																
[Kumar et al. 2021]	✓																
[Zhang et al. 2021]	✓																
[Chow and Bond 2022]	✓																
[Coats 2022]	✓																
[Eggleston and O'Connor 2022]	✓																✓
[Fuad and Al-Yahya 2022]	✓																
[Harris et al. 2022]	✓																
[Husain et al. 2022]	✓																
[Inoue et al. 2022]	✓																
[Kanjirang et al. 2022]	✓																
[Kaseb and Farouk 2022]	✓																
[Käsen et al. 2022]	✓																
[Liu et al. 2022]	✓																
[Lu et al. 2022]	✓																
[Okpala et al. 2022]	✓																
[Olabisi et al. 2022]	✓																
[Rajai and Enmasser 2022]	✓																
[Saadany et al. 2022]	✓																
[Artemova and Plank 2023]	✓																
[Held et al. 2023]	✓																
[Kantharuban et al. 2023]	✓																
[Kuparinen et al. 2023]	✓																
[Lameli and Schönberg 2023]	✓																
[Le and Luu 2023]	✓																
[Lent et al. 2023]	✓																
[Maurya et al. 2023]	✓																
[Piiss et al. 2023]	✓																
[Ramponi and Casula 2023]	✓																✓
[Riley et al. 2023]	✓																
[Zhan et al. 2023]	✓																
[Ziems et al. 2023]	✓																

Table 2. State of NLP research on Dialects.



Training Datasets	Model		Evaluation	
<p><b>Labeled Datasets</b></p> <ul style="list-style-type: none"> <li>- Geo-located</li> <li>- Keyword-based</li> <li>- Native annotation</li> <li>- Semi-supervised creation</li> </ul> <p><b>Treebanks &amp; Lexicons</b></p> <ul style="list-style-type: none"> <li>- Manual annotation</li> <li>- Co-occurrence using statistical methods</li> </ul>	<p><b>NLP Tasks</b></p> <ul style="list-style-type: none"> <li>- Dialect classification</li> <li>- Sentiment analysis</li> <li>- Parsing</li> <li>- Machine translation</li> <li>- Natural language entailment</li> </ul>	<p><b>Dialect transformation</b></p> <ul style="list-style-type: none"> <li>- Perturbation rules</li> <li>- Gramme</li> <li>- Lattice path</li> </ul> <p><b>Dialect invariance</b></p> <ul style="list-style-type: none"> <li>- Character embeddings</li> </ul>	<p><b>Dialect awareness</b></p> <ul style="list-style-type: none"> <li>- Dialect-specific components/neural layers</li> <li>- Adversarial learning</li> <li>- Multi-task prediction of dialect and task-specific labels</li> <li>- Learning adapters</li> </ul>	<p><b>Dialectic datasets</b></p> <p><b>Correlation with downstream tasks</b></p> <ul style="list-style-type: none"> <li>Health monitoring</li> <li>Sociological factors</li> </ul>

Fig. 2. An Overview of Approaches in terms of NLP for Dialects.

- (1) **Training resources:** Labeled datasets, treebanks and lexicons in dialects of a language have been reported in the past. This includes datasets with dialect labels along with additional task-specific labels, where the task is an NLP research problem.
- (2) **Models:** Models have been enhanced with several techniques, as may be typical of the time of the research. The fact that dialect-aware NLP can benefit from model adaptations and not dataset replacement alone is a key point of the survey.
- (3) **Evaluation datasets:** NLP techniques evaluated on datasets in dialects have peculiar observations. Language identification classifiers produce lower performance when the text is in a dialect of a language. The performance of LLMs on dialectic datasets is positively correlated with socio-economic factors.

Figure 2 shows an overview of the approaches in terms of NLP for dialects. There have been different approaches to create labeled datasets, tree-banks and lexicons. In terms of models, past work varies in terms of NLP tasks and the way dialectic adaptation is handled: dialect transformation (where data is translated between dialects for the purpose of processing), dialect invariance (where models are made invariant to dialects) and dialect awareness (where models include dialect-specific components). Finally, we also describe dialectic datasets and resultant evaluations on downstream tasks including applications such as health monitoring. The next sections are centered around resources, NLU and NLG tasks keeping in view these aspects.

## 4 RESOURCES

Being a data-driven field, NLP techniques rely on resources such as lexicons and textual datasets. In this section, we describe ways in which dialectic datasets have been created.

### 4.1 Dialectic Lexicons

Dialectic lexicons correspond to word lists or word mappings about a dialect. Past work in the creation of dialectic lexicons lies in three categories: the use of online dictionaries, and the use of textual corpora.

*4.1.1 Online dictionaries.* [Azouaou and Guellil 2017] create a lexicon of words mapping French and its Algerian dialect. They use online dictionaries along with a combination of manual and automatic methods to enhance the lexicon. This includes many-to-one mapping of words in the

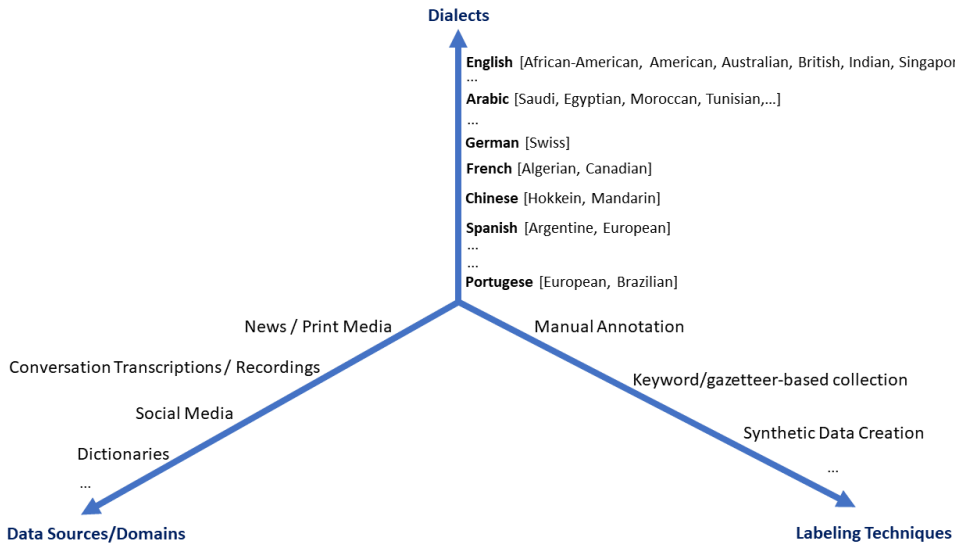


Fig. 3. Overview of dataset creation approaches.

two sets. Similarly, [Boujelbane et al. 2013] build bilingual lexicons to create Tunisian dialectic corpora to adapt n-gram models for statistical machine translation.

**4.1.2 Textual corpora.** [Abdul-Mageed and Diab 2014] present a lexicon of words in dialects of Arabic including Levantine and Egyptian dialects. They present two lexicons: adjectives from news articles and common words in online chat forums. The words are labeled with a combination of manual and automatic techniques, the latter based on statistical techniques such as pointwise mutual information. Similarly, [Burghardt et al. 2016] use the web as a corpus to create a lexicon for the Bavarian dialect of German. Starting with a corpus of Facebook comments, they provide a rule-based algorithm to create the lexicon. They first extract unique text forms, and then filter non-dialect words based on the Dortmund chat corpus. [Harrat et al. 2018; Younes et al. 2020] discuss various existing resources for the Maghrebi Arabic dialects (MAD) including annotated corpora for language identification, and morpho-syntactic analysis. MAD include principally Algerian Arabic, Moroccan Arabic and Tunisian Arabic.

## 4.2 Dialectic Datasets

Figure 3 summarises dialectic datasets in terms of three dimensions: dialects, labeling techniques and data sources. Several data sources such as social media, conversation transcripts and so on have been used. Similarly, past work has also dealt with dialects of languages spoken around the world. In terms of procuring and labeling these datasets, the following methods have been used:

**4.2.1 Recruit native speakers.** : [Estival et al. 2014] create a dataset of audio-visual recordings of 1000 speakers of Australian English. The dataset is accompanied by a transcript which was manually created for 100 speakers. Similarly, [Riley et al. 2023] create a parallel corpus of English sentences and two dialects each of Portuguese and Chinese with the help of native speakers of these dialects.

**4.2.2 Perturbation.** : [Ziems et al. 2022] evaluate natural language understanding for African-American English. They design rules to perturb the dataset from Standard American English

to African-American English. They then get them validated by native speakers. [Ziems et al. 2023] present Multi-VALUE, a suite of resources to evaluate fairness of LLMs by creating dialectic variations of a dataset. The suite provides mechanisms to generate 50 dialects of English by applying a set of perturbations.

**4.2.3 Keywords.** : [Wang et al. 2017] create a dataset of Singaporean English sentences by searching for typical Singaporean English terms in online forums. [Ramponi and Casula 2023] take a *complementary* approach to create a dataset of tweets in dialects of Italian. They use location-based search to obtain the set of tweets from different regions of interest from within Italy. Following this, they use out-of-vocabulary words to identify words that are indicative of geographical regions and, as a result, dialects. In the case of social media, *hashtags* can be used to obtain datasets in certain dialects. [Scherrer et al. 2023] take advantage of dialect awareness week in Finland. They use a hashtag indicating usage of dialects in order to collect tweets in different dialects of Finnish.

**4.2.4 Location.** : Data from particular geographics can be extracted using filters (where the location is known) or inference (where it is not known). [Jurgens et al. 2017] use location-based filters available on Twitter at the time. They use language identification classifiers to predict the language and identify dialectic users. [Husain et al. 2022] obtain tweets from Kuwait to create a dataset of tweets in the Kuwaiti dialect of Arabic. [Coats 2022] create an unlabeled dataset of Youtube comments. They start with a list of councils in Australia, extract official Youtube channels and retrieve comments. They manually validate the correctness of the channels. When working with geographically dispersed dialects, *sampling* may also be used. [Dunn and Adams 2020] create a Web-based corpus in different dialects of the corpus by sampling sentences from different countries. The goal is to build a Web-based corpora where the number of instances are reflective of the population of speakers in a country. The paper states that such a geography-aware corpus can lead to geography-aware representations when language models are trained on them. Some researchers perform location *inference* using computational techniques. [Blodgett et al. 2018] use a demographically-aligned topic model that predicts a demographic for a tweet. They use it as a label followed by manual validation.

**4.2.5 Dialect-aware annotation.** : One such example is by [Sap et al. 2019]. They examine racial bias towards African-American English in the case of hate speech detection. They propose race and dialect priming in order to improve the quality of annotation. In order to prime the annotators, they propose to ask two questions: (a) is the tweet offensive to them, and (b) is the tweet offensive to anyone. The dialect and race of the speaker are shown to the annotators.

## 5 NATURAL LANGUAGE UNDERSTANDING (NLU)

This section covers NLU approaches centered around dialects. This includes approaches for NLP tasks such as dialect identification, sentiment analysis, morphosyntactic analysis and parsing. We also describe approaches reported on NLU benchmarks which cover multiple tasks.

### 5.1 Dialect Identification

The most commonly researched task in the scope of this paper is dialect identification. Dialect identification deals with the prediction of the dialect of an input text. Early approaches to dialect identification employed distance-based metrics, namely, Levenshtein, Manhattan, and Euclidean distance with clustering and training a Kohonen map<sup>13</sup> [Nerbonne and Heeringa 1997, 2002]. They indicate that feature representations are more sensitive, and that, Manhattan distance and

<sup>13</sup>A Kohonen map is a neural network in which concepts are plotted during a training procedure. Similar concepts are plotted near one another

Paper	Source languages
[Farha and Magdy 2022]	Dialects of Arabic
[Lui and Cook 2013]	Dialects of English
[Simaki et al. 2017]	Dialects of English
[Hanani and Naser 2020]	Dialect of Arabic
[Goswami et al. 2020]	Dialect of German
[Hou and Huang 2020]	Dialects of Chinese
[Abdul-Mageed et al. 2018]	Dialects of Arabic
[Blodgett et al. 2016]	Dialect of English
[Barnes et al. 2021]	Dialects of Norwegian
[Aji et al. 2022]	Dialects of Indonesian
[Ramponi and Casula 2023]	Dialects of Italian

Table 3. Language distribution for dialect detection.

Euclidean distance are good measures of phonetic overlap. [Elnagar et al. 2021] is a systematic review of identification of dialects of Arabic. For dialects of Arabic, lexical resources such as lexicons and tree banks, and models using SVM or sequential neural layers like BiLSTM have been reported. [Jauhiainen et al. 2019] is a survey of automatic language identification. They mention that dialect detection may be more difficult than language detection since dialects may have lexical or syntactic overlap. In doing so, the survey does not make a distinction between languages and dialects - and treats different dialects as different class labels, while still maintaining a classification approach. However, one sees challenges in this regard. [Blodgett et al. 2016] use an extension of an LDA-based model for language identification. The language identification classifier is expected to predict dialects of English as English. However, the results show that the classifier trained on ‘standard English’ data may not work as well for dialectic variations: as seen in the case of African-American English. [Boujou et al. 2021] benchmark a novel dataset of 50,000 tweets for five dialects of Arabic- Algerian, Lebanon, Morocco, Tunisian, and Egyptian, and also a present baseline benchmark which utilizes classical machine learning.

We now describe details of past work in dialect identification in terms of shared tasks, datasets, and pre-deep learning and deep learning-based approaches.

**5.1.1 Shared tasks.** Shared tasks have accelerated past work in dialect identification. These have been primarily led by Workshop on NLP for Similar Languages, Varieties and Dialects, also known as VarDial. [Zampieri et al. 2015] is a 2015 shared task to discriminate between similar languages, including American and British English; and Argentinian Spanish and Castilian Spanish. [Zampieri et al. 2014] is the 2014 version of the task which includes Brazilian Portuguese and European Portuguese in addition to the previous. In 2016 version of the same shared task, [Malmasi et al. 2016] introduced French from Canada and from France to the set. In addition, they also added a subtask for dialect classification of Arabic, namely for the dialects: Modern Standard Arabic (MSA) and the Egyptian (EGY), Gulf (GLF), Levantine (LAV) and North African (NOR) dialects. [Goutte et al. 2016] summarises the findings from the past versions of the shared task from 2014-2016. [Zampieri et al. 2019] present a report of a dialect identification shared task from 2019. Their datasets include dialects of German, Chinese, Romanian along with Cuneiform language identification.

**5.1.2 Datasets.** Table 3 shows datasets labeled with different dialects. [Aji et al. 2022] report a dataset for several languages and dialects spoken in Indonesia. They observe that language

identification works well for certain dialects (Ngoko-Central dialect of Javanese, for example). The paper also discusses code-mixing and orthography variations in these languages. [Dunn 2019] reports dialect identification on 14 national varieties of English. They show that cross-domain classification (CommonCrawl versus Twitter) also performs poorly. [Cotterell and Callison-Burch 2014] present a multi-dialect, multi-genre corpus of news comments and tweets written in dialects of Arabic. The tweets are manually annotated for dialect identification on MTurk. [Ramponi and Casula 2023] present a benchmark dataset for dialects of Italian. The benchmark is named as DIATOPIT. There has been recent work on creating a corpus of Norwegian dialect data by [Barnes et al. 2021]. [Alshutayri and Atwell 2018] present a large (200K+ instances) corpus for Arabic dialects and Standard Arabic. The data is sourced largely from tweets but also includes comments from newspapers, and Facebook. The data is also being annotated for dialect identification and contains 24K annotated documents. [Le and Luu 2023] present a parallel corpus for dialects of Vietnamese.

*5.1.3 Feature-based approaches.* We now highlight different kinds of features used for dialect identification.

- (1) **Acoustic features:** [Chitturi and Hansen 2008] is an early work in dialect identification from audio recordings of podcasts in Australian, UK and American English. They use n-gram-based classifiers on the transcripts of the recordings along with Gaussian mixture model-based classifiers on acoustic features. In the language of today, this would be called a multimodal classifier.
- (2) **Phonological features:** While acoustic features are derived from audio data, phonological features are based on markers in the written scripts. [Darwish et al. 2014] use lexical, morphological and phonological features in a random forest classifier to detect dialects of Arabic spoken in a geographical region. They also use a lexicon of dialectic Egyptian words.
- (3) **Linguistic features:** [Doğruöz and Nakov 2014] present a method to predict dialects of Turkish by using light verb constructions. They use a statistical classifier based on verb-based features (base word, verb order, affixes, etc.) for the task.

The combinations of the above set of features have also been reported. While [Hanani and Naser 2020] work on the detection of dialects from speech, they also use word-level n-gram features.

Limited pre-deep learning work exists in the context of English. [Lui and Cook 2013] is an early work in the detection of dialects of English. Specifically, the paper focuses on Australian, British and Canadian English. Their baseline is the LangID classifier [Lui and Baldwin 2012] where dialects are treated as individual languages. They experiment with classifiers using features such as n-grams and POS-n-grams. This includes a distribution over function words and those in a vocabulary, akin to a clustering algorithm. [Simaki et al. 2017] also presents statistical models (based on SVM, decision tree and so on) for dialects of English: US, UK, AUS, CAN and so on. They use linguistic, POS-tag-based and lexicon-based features.

*5.1.4 Deep learning-based Approaches.* Deep learning-based approaches for dialect classification span three alternatives: train embeddings to reflect dialectic variations, use end-to-end LLMs, or predict dialect as a result of inference over dialect features.

**Embeddings in focus:** [Abdul-Mageed et al. 2018] label tweets with 10 dialects of Arabic. The city is considered the dialectic granularity. The analysis compares dialectic variants by looking at word embeddings of words across different dialects. They use word2vec representations to show how dialectic words are captured. [Goswami et al. 2020] build character-to-sentence embeddings to represent words of different dialects. Unsupervised loss is computed in order to generate clusters of representations. While they also test on language identification, the dialect identification part is

done on Swiss German dialect. [Jurgens et al. 2017] use a character-based *seq2seq* model to map dialects. The models used for language identification are RNNs with GRU. [Crisciolo and Aluisio 2017] use character n-grams to identify language groups. This is followed by convolutional neural network-based dialect classifiers for each language group.

**Fine-tuning LLMs:** [Ramponi and Casula 2023] experiment with multiple models including statistical and neural. The fine-tuned ALBERTo model performs the best among umbERTo, mBERT and XLM-R. [Obeid et al. 2020] present CAMEL: a python toolkit for Arabic language processing. It contains a dialect identifier that gives a distribution over multiple dialects. They use dialectic guidelines provided in [Elfardy and Diab 2012].

**Detecting dialect features:** [Demszky et al. 2020] introduce an approach for dialect classification using a novel multi-task approach that employs dialect feature detection. They train models using two multi-task learning-based approaches using a small number of minimal pairs. They evaluate the output based on 22 dialectical features based on Indian English and demonstrate that such models show the capability of learning to identify features with high accuracy. They show the efficacy of this task by applying it for dialect identification, and by providing a measure of dialect density.

## 5.2 Sentiment Analysis

Sentiment analysis is the NLU task of prediction of sentiment polarity of a text. Sentiment analysis encompasses several related tasks such as sarcasm classification and target-specific sentiment analysis. We discuss past work in sentiment analysis along four directions: experiences from annotation (which highlights the challenge of dialects for sentiment analysis), dialect-invariant models, dialect-aware models and finally de-biasing of sentiment analysis models as a post-processing step. Table 4 summarises approaches for sentiment analysis.

**5.2.1 Datasets & Annotation.** Several datasets in Arabic sentiment analysis for dialects have been reported such as Moroccan [Oussous et al. 2020] and Levantine [Baly et al. 2019]. Dialects can have an impact on annotation itself. [Farha and Magdy 2022] show that dialect familiarity helps sarcasm annotation. [Mdhaffar et al. 2017] create a dataset of 17000 Facebook comments labeled with sentiment in Tunisian dialect of Arabic. [Assiri et al. 2018] present a sentiment-labeled lexicon of words in the Saudi dialect of Arabic, and use simple counting-based sentiment analysis. [Husain et al. 2022] use weakly supervised labels for sentiment analysis of tweets in the Kuwaiti dialect of Arabic. The labels are then manually validated and updated.

**5.2.2 Dialect-aware representations.** [Farha and Magdy 2022] train BERT-based models for sarcasm detection on data annotated by either of the two groups: those familiar with the dialect and those not. They show that familiarity of dialect improves the quality of the models trained on such a dataset. As a result, representations that capture dialects have been used for sentiment analysis. [Mdhaffar et al. 2017] present models based on SVM and multi-layer perceptron (MLP). [Mulki et al. 2019] use a syntax-ignorant n-gram composition to create embeddings. The classifier model is a dense neural network that works on the addition of word embeddings, with a softmax at the end. [Guellil et al. 2021] propose ‘one’ model for sentiment classification in different dialects of Arabic. They use transliteration to map dialects to Standard Arabic. The sentiment analysis model itself uses word2vec features with statistical classifier. Finally, [Husain et al. 2022] present statistical models based on SVM along with Transformers-based models like BERT.

**5.2.3 Incorporating dialect information in sentiment prediction.** [El Mekki et al. 2021] use domain adaptation for sentiment analysis of dialects. Using representations from a BERT encoder, they use two classifiers: sentiment classifier and dialect classifier. The output of the two is later combined for the overall prediction. While this is a two-channel approach, the representation used for the task

has also been used to predict dialect of the language. One such example is [Okpala et al. 2022] who present an approach for hate speech detection using African-American English (AAE). In order to do so, they re-train BERT with AAE tweets. Finally adversarial training to regulate debiasing of the hate speech classifier. Specifically, the adversary takes the final representation learned by the hate-speech classifier; and learns to predict the dialect from it. [Kaseb and Farouk 2022] present a dialect-aware approach for sarcasm detection called the SAIDS model. SAID uses MARBERT to detect dialect and sarcasm. Following that, MARBERT along with sarcasm and dialect output are used to detect sentiment. Evaluated on dialects of Arabic, SAID uses backpropagation only for prediction with respect to the BERT base model. It does not flow through sentiment $\leftrightarrow$ sarcasm or sentiment $\leftrightarrow$ dialect.

*5.2.4 De-biasing sentiment analysis models.* Making sentiment analysis agnostic to dialects involves removing dialectic biases in the resultant models. A work of this nature is by [Ball-Burack et al. 2021] who apply adversarial debiasing on resampled data for harmful tweet detection of tweets written in African American English. Resampling of the data uses a metric for margin of confidence which selects the set of tweets that are most likely to be mis-classified. Adversarial debiasing involves training an adversary network to debias the classifier by including the adversary network's loss. Similarly, [Mozafari et al. 2020] report results on hate speech detection from African-American and Standard American tweets. They re-weight instances based on the presence of phrases that they may highlight racial bias. They fine-tune BERT for the task. Finally, [Zhang et al. 2021] present an approach to reduce spurious correlation between two attributes: toxicity and African-American Vernacular English. They construct triplets of sentences where the first pair have the same toxicity label and the first and third have the same dialect label. The objective function of the model consists of a triplet loss over these triplets, and a disentanglement loss that ensures the masks for the true attributes are well-separated. Similarly, graphical models have been used to infer socio-cultural norms since they are closely associated with dialectic variations based on the language and cultural background of the speaker. [Moghimifar et al. 2023] present a Markov model to discover socio-cultural norms in emotion classification.

### 5.3 Morphosyntactic analysis

Morphosyntactic analysis deals with linguistic tasks such as POS tagging and morphological analysis. We now describe past work that deals with dialectic variations, as summarised in Table 5.

*5.3.1 Classical approaches.* [Habash and Rambow 2006] is a seminal morphological analyser for dialects of Arabic called MAGEAD. Using morphological rewrite rules, they show how a morphological analyser can be adapted for dialects of a language. [Jørgensen et al. 2015] evaluate on a dataset of African-American Vernacular English and show that the then-prevalent POS taggers perform significantly worse. [Darwish et al. 2018] present a CRF-based POS tagger for dialects of Arabic. The POS tagger is trained on a small set of tweets using features derived from the dialects of interest. These features are progressive and negation particles.

*5.3.2 Deep learning-based approaches.* [Inoue et al. 2022] use CamelBERT trained on Modern Standard Arabic fine-tuned on dialect-specific datasets for morphosyntactic analysis. They observe that training using high-resource dialects helps low-resource dialects as well. In the context of Indic languages, [Bafna et al. 2023] explore POS tagging for 5 Indic dialects by focusing on Hindi-aware LLM adaptation via small dialectic monolingual corpora.

### 5.4 Parsing

Parsing involves the creation of semantic parse trees from text. Past work in parsing texts written in dialects of a language lies in three categories. The first category uses an existing parser on a

Paper	Dialects	Modelling Approach
[Mdhaffar et al. 2017]	Dialects of Arabic	SVM/MLP
[Mulki et al. 2019]	Dialects of Arabic	Syntax-ignorant composition to learn word embeddings
[Mozafari et al. 2020]	African-American English	Re-weight instances based on racially biased phrases for hate speech detection
[El Mekki et al. 2021]	Dialects of Arabic	Infer dialect and sentiment label using two channels from BERT encoder
[Guellil et al. 2021]	Dialects of Arabic	Transliteration to map to standard version
[Kaseb and Farouk 2022]	Dialects of Arabic	Infer dialect and sarcasm label; limited backpropagation to maintain label dependency
[Okpala et al. 2022]	African-American English	Adversarial training to debias dialectic variation
[Moghimifar et al. 2023]	English	Socio-cultural norms are inferred using a Markov model variation

Table 4. Sentiment Analysis Approaches for Dialectic Datasets.

Paper	Dialects	Highlight
[Habash and Rambow 2006]	Dialects of Arabic	Rewrite rules to adapt morph analysers
[Jørgensen et al. 2015]	African-American English	POS taggers perform worse for the dialect
[Darwish et al. 2018]	Arabic	CRF-based POS tagger; Linguistic features
[Inoue et al. 2022]	Arabic	Fine-tuned LLMs
[Bafna et al. 2023]	Indic Languages	Fine-tuned LLMs

Table 5. Approaches for Morphological Analysis Focusing on Dialects. Highlight-&gt; Approach or Key Finding.

dataset in a dialect of interest. The focus of such work is to create a baseline performance of popular parsers. The second category provides approaches to mitigate the bias of existing parsers towards texts in the dialect of a language. The third category creates a new parser for the dialect.

*5.4.1 Use of existing parsers.* : [Eggleston and O'Connor 2022] parse tweets in Standard American English and African-American English and use it to analyse social attributes of an entity, as per sentiment expressed in the tweets. [Kåsen et al. 2022] create a tree bank of sentences in the Bokmål variety of Norwegian. They present their results on the UUParser, an existing parser for Norwegian. [Roy et al. 2020] present an analysis using Stanford parser and Allen NLP parser on parsing of news headlines in Indian English. [Scannell 2020] create a treebank for Manx Gaelic and compare the performance of existing classifiers with Irish Gaelic and Scottish Gaelic.

*5.4.2 Adaptation of an existing parser.* : [Chiang et al. 2006] show how parsing of Arabic dialects can be done by a sentence transduction approach. This approach parses the standardised version



Paper	Dialects	Approach
[Ziems et al. 2022]	African-American English	Perturbation to create variants
[Dacon et al. 2022]	African-American English	Adversarial learning
[Held et al. 2023]	Dialects of English	Contrastive loss, Morphosyntactic loss
[Xiao et al. 2023]	Dialects of English	Hypernetworks as LoRA adapters

Table 6. Dialect-aware approaches evaluated on NLU benchmarks.

of a dialectic sentence, and then link it to the original sentence. The standardisation is achieved using transduction, akin to n-gram decoding. However, [Blodgett et al. 2018] uses neural networks and presents an approach to dependency parsing for African-American English. This approach uses two neural parsers, which are modified with the word embeddings used for initialisation. The word embeddings are trained on the standard and the dialect-specific datasets. Further, [Wang et al. 2017] create a dependency parser for Singaporean English. This approach uses a base parser for standard English and stacks it with a series of BiLSTM layers known as the ‘feature stack’ to extract relevant features, and an MLP with an output layer help produce dependency-parsed output. [Zhao et al. 2020] use a treebank of learner English sentences labeled with POS tags and dependency information. They propose a factorisation-based parser that first predicts nodes followed by edges in a dependency parse. [Dou et al. 2023] evaluates various parsers designed for converting text to SQL, focusing on a multilingual benchmark that covers dialects from seven different languages. This research is significant for its emphasis on semantic parsing, differing from the aforementioned dependency parsing works.

*5.4.3 Development of a new parser.* : [Bowers et al. 2017] present a finite-state machine-based parser for the endangered Odawa dialect of Ojibwe spoken in Canada and neighbouring countries. This approach uses a phonological module composed with a morphological module where morphological strings are modified by the phonology until they match surface forms of the language.

## 5.5 NLU Benchmarks

Finally, NLU benchmarks such as GLUE have become popular in NLP research. They provide a set of datasets for several NLP tasks. This section discusses dialectic studies evaluated on benchmarks for NLU tasks. [Ziems et al. 2022] show a drop in performance on 7 GLUE tasks including SST-2, SST-B. Drop in performance is observed. For SST-2 it is 1.5-2% drop using fine-tuned RoBERTa.

[Dacon et al. 2022] work with the African-American English. They first propose CodeSwitch, a rule-based method of perturbing a sentence from standard American English to African-American English. They create perturbed versions of the dataset using CodeSwitch and manually evaluate it. They finally evaluate their method on NLI. In order to do so, they use adversarial learning that ensures that the predicted label is same if either the SAE or AFE sentences are provided as the input. They refer to this as disentanglement of language style.

[Held et al. 2023] model natural language understanding for dialects as a dialect adaptation task. Using Multi-VALUE, they create African-American English variations of the GLUE benchmark (which is primarily written in Standard American English). Following that, they adapt a model pre-trained on Standard American English. To do so, they use: (a) a contrastive loss to ensure the representation of a standard sentence and its dialectic version is as close as possible; (b) a morphosyntactic loss based on word-level alignment between the standard and dialectic sentences. Their results show improved robustness on 4 dialects based on the GLUE benchmark.

Paper	Dialect	Approach
<b>Summarisation</b>		
[Olabisi et al. 2022]	African-American / Hispanic English	Representations-based clustering & obtain summaries separately.
[Keswani and Celis 2021]	English Dialects	Diversity-representative sentences & weigh them for summary generation
<b>Text generation</b>		
[Sun et al. 2023]	English Dialects	Towards dialect-robust metrics for text generation

Table 7. Representative Examples for sequence-to-sequence NLP tasks (except machine translation).

A recent work by [Xiao et al. 2023] shows how low-rank adaptation (LoRA) can use linguistic knowledge of dialects to improve zero-shot performance on NLU tasks. They integrate hypernetworks with LoRA adapters for dialect adaptation. Experts encode linguistic information in the form of feature vectors. A hypernetwork then learns to generate adapter weights for LoRA from the feature vectors. They demonstrate the impact of their fine-tuning approach on several GLUE tasks such as MNLI, RTE and so on. The dataset consists of variants of the GLUE benchmark for five dialects: African American Vernacular English (AAVE), Indian English (IndE), Nigerian English (NgE), Colloquial Singaporean English (CollSgE), and Chicano English (ChcE). Similarly, [Liu et al. 2023] use dynamic aggregation of linguistic rules to adapt LLMs to multiple dialects. They first create a synthetic dataset of linguistic transformations using LLM probing. Following that, they train a set of feature adapters to generalise across multiple dialects of interest. They present their evaluation of multiple dialects of English.

## 6 NATURAL LANGUAGE GENERATION (NLG)

The previous section showed that NLU for dialects has been primarily focused on tasks like identification of dialects, and sentiment analysis. We now present approaches in NLG. NLG deals with sequence-to-sequence (*seq2seq*) tasks in NLP which take a sequence as input and produce a sequence. Some examples of such problems are summarisation, question answering and machine translation, and are described in Table 7. While the situation in the case of NLU was already dire, our survey indicates that for NLG, it is even worse. We will now discuss NLP approaches that deal with dialects of a language in the context of *seq2seq* problems.

Two works reflect advances in the context of *seq2seq* problems:

- (1) **Making evaluation metrics dialect-aware:** [Sun et al. 2023] state that metrics used to measure text generation may penalise outputs in certain dialects. They propose a metric named NANO which allows perturbations in the generated output. They show that models pretrained with NANO as the metric can be helpful for dialect-robustness.
- (2) **Creating dialectic variants of datasets for benchmarking:** [Ziems et al. 2023] present Multi-VALUE, a library that creates dialectic variations of datasets based on a set of manually created rules. They create variants of benchmark datasets, and evaluate the variants for several *seq2seq* tasks including machine translation, question answering and so on. The models for evaluation are based on modern LLMs such as BERT, ROBERTA, BART and T5. The library provides a useful resource as well as insights for dialect-aware benchmarking in the future.

## 6.1 Summarisation

Past work in summarisation, although limited, states that dialect labels may not be explicitly necessary. However, a review of Arabic text summarisation by [Elsaid et al. 2022] state the use of “dialect period frameworks” to incorporate semantic information about dialects. In the case of multi-document summarisation, clustering of sentences in the input set is a predominant paradigm. Two such works are noteworthy:

- (1) [Olabisi et al. 2022] analyse the diversity of dialects in multi-document summarisation of social media posts. They present a dataset that contains summaries of a collection tweets written in three dialects: African-American (AA) English, Hispanic English, and White English. They use extractive summarisation using LONGFORMER-EXT and abstractive summarisation using BART and T5. In order to bring diversity-awareness in summarisation, they create automatic clusters of input documents based on semantic attributes. They follow a 2-stage approach where the summarisers are separately applied, and the resultant outputs are combined again using a summariser.
- (2) [Keswani and Celis 2021] examine the role of dialect diversity on multi-tweet summarisation. They use a variety of summarisers: typical traditional summarisers like TF-IDF, TextRank and LexRank, and SummaRunner (a neural summariser that treats summarisation as a sequence classification task). They create a control set: a subset of sentences that represent different dialects in the set of sentences. They introduce a bias mitigation procedure that introduces dialect-awareness in summaries using a parameter that is weighted to increase the score of dialect-diverse sentences in the dialect set.

## 6.2 Machine Translation

Compared to summarisation, machine translation has been studied a bit more. Recent work is broadly divided into two categories: (i) translation between dialects of the same language, and (ii) translation between the dialect of a language and another language. In the rest of this section, we cover the approaches in these categories.

*6.2.1 MT between dialects of the same language.* The primary goal of inter-dialect translation is the dissemination of information available between a standard dialect and a non-standard one. In this context, the following works are relevant. Mapping from less used dialects to their most common versions is called **dialect normalization**. One such work by Kuparinen et al. [2023] provides a dialect normalization dataset in Swiss German, Slovene, Finnish, and Norwegian.

**Harnessing pre-trained models:** Le and Luu [2023] show that models based on  $BART_{pho}$  perform well for dialect normalisation in dialects of Vietnamese. This indicates that denoising-based pre-trained models can be a good source for dialect data generation owing to their infilling capabilities.

**Character level modeling:** [Abe et al. 2018] conduct Japanese dialect translation where they use NMT to translate from dialect to standard Japanese using character RNN trained on small datasets collected as a part of their work. [Honnet et al. 2018] additionally suggest that normalization is an important aspect for translating between Swiss German dialects, which is achievable via character-level models. Kuparinen et al. [2023] further show that sliding-window-based approaches are useful since dialect translation does not need the entire sentence-level context.

**Perturbation-based regularization:** [Liu et al. 2022] present a *seq2seq* approach for machine translation of Singaporean English to standard English. They use word perturbation and sentence perturbation to prevent overfitting of lexical features. [Maurya et al. 2023] used a similar approach for Indian dialects.

**Leveraging ASR:** [Plüss et al. 2023] report a dataset of speech transcripts that map Standard German sentences to Swiss German sentences. They use XLS-R to train a system for automatic

speech recognition and report a high average BLEU of 74.7. Their model reports significant gains over two other Swiss-German ASR test sets, indicating the efficacy of this corpus.

**Code-mixed training:** [Lu et al. 2022] use XLM for Translation between Hokkein-Mandarin code-mixed text. They observe that continuous training with code-mixed data enables monolingual language models to provide better performance when applied to code-mixed tasks.

**Data Creation for MT Between Dialects:** Zbib et al. [2012] and Meftouh et al. [2015] also focus on multi-dialect MT data collection for Arabic, which is, once again, to be noted as one of the most studied languages for dialects. Xu et al. [2015] use a Hidden Markov-based model to create word alignment between dialects of Chinese: Mainland Chinese, Hong Kong Chinese, and Taiwan Chinese. The outcome is a monolingual corpus that contains corresponding words used in the three dialects. Their approach was shown to be effective for three different alignment mapping cases. Rather than use word alignment [Hassani 2017] work on Kurdish dialectic MT using dictionaries that show that having limited to no parallel corpora is not a huge barrier for inter-dialect translation.

All these works emphasize that a small amount of parallel data between dialects is always important; however, data synthesis and transfer learning from a high-resource dialect is always impactful, especially in conjunction with character and word level perturbation methods.

*6.2.2 MT between dialects and another language.* The second category, involving the harder challenge of machine translation between a dialect and another language, has received far more attention. We cover notable works in this section.

**Dialect pivoting:** An early work in this regard is by [Paul et al. 2011]. They present a pivot-based MT approach for the translation of four dialects of Japanese, namely Kumamoto, Kyoto, Okinawa, and Osaka. In order to map sentences across dialects, they use a character-based generative graphical model. They then translate the dialects into four Indo-European languages, using standardised Japanese as the pivot language. [Jeblee et al. 2014] focus on using modern standard Arabic as a pivot when translating from English to the Egyptian Arabic dialect.

**Unsupervised segmentation:** Different from Abe et al. [2011] who focus on characters, [Al-Mannai et al. 2014] work on Arabic dialectic translation which shows that unsupervised word segmentation helps for translation into English.

**Evaluating existing translators on dialectic datasets:** [Kantharuban et al. 2023] show the performance of MT between English and dialects of seven languages. Using state-of-the-art MT systems such as Google NMT and Meta NLLB, they evaluate MT in both directions (to and from English). They report a drastic drop in BLEU for dialects of German, Portuguese and Bengali.

**Using inferred dialectic labels to guide translation:** [Sun et al. 2023] add language-dialect information as predicted by a language identifier as an input when training an MT system. They further improve the metrics for robust evaluation of text generation systems for different languages and dialects. They report their results on several dialects of English, Chinese, Portuguese and so on. They use few-shot prompting to create semantic perturbations to train T5. The results show that dialect-awareness improves the performance of translation. [Shapiro and Duh 2019] explore a multidialect system and identify when dialectic identification is useful. [Tahssin et al. 2020] focus on dialect identification itself using AraBERT models. [Salloum et al. 2014] SMT work that focuses on sentence-level dialect identification for MT model selection where the MT model is optimized for that dialect.

**Learning through exemplars:** Few-shot learning involves the use of examples in a prompt to guide the generation through a language model. [Riley et al. 2023] present a few-shot machine translation approach for translation between English and two variants of Portuguese and Chinese. The parallel corpus is manually created by native speakers. The exemplars used in the dataset are from the specific dialect in order to obtain translations of English sentences.

**User-generated Content:** User-generated content is often mistranslated on social media, especially, for low-resource languages like dialectal Arabic. [Saadany et al. 2022] train a Transformer to translate from Dialectal Arabic to English where they focus on challenges in translation of user-generated content, and propose a sentiment-aware evaluation metric for translation. They discuss results on multiple test sets, including a hand-crafted test set, and analyze the performance of a semi-supervised approach compared to a baseline NMT system, a pivoting-based system, and Google Translate.

**Use of multiple translation models:** Translation models that translate between the standard version and a dialect can assist machine translation. [Kumar et al. 2021] show an approach for MT from English to Ukrainian, Belarusian, Nynorsk, and Arabic dialects. They use two models: a dialect-to-standard translation model, and a standard source-to-target language translation model.

**Data Creation for MT of Dialect to Another Language:** [Hassan et al. 2017] explore synthetic data creation using word pairs between dialects based on embeddings. They take seed data, transform it into its dialectic variant and now have a dialectic parallel corpus. Similarly, [Almansor and Al-Ani 2017] focus on using monolingual data and tiny parallel corpora in conjunction between cross-dialectic embeddings to improve MT between dialects. Sajjad et al. [2020] take dialect MT evaluation further and focus on multi-domain coarse-grained analysis of dialects of Arabic via their AraBench benchmark.

*6.2.3 Dialect MT in Shared Tasks.* Given that most dialects are spoken and not written, the IWSLT workshop, which focuses on spoken language translation has been conducting shared tasks on dialects under the banner of low-resource MT. The 2022<sup>14</sup> and 2023<sup>15</sup> workshops featured dialectic speech translation, with resources for text-text as well as speech-text translation. The focus, as is typically the case, is on dialects of Arabic like Tunisian, Egyptian and Moroccan. The shared tasks are an excellent source of datasets and benchmarks for dialectic MT. The 2024<sup>16</sup> edition of IWSLT is expected to focus on North Levantine Arabic.

### 6.3 Dialogue Systems

Dialogue systems, crucial in facilitating human-computer interaction, are categorized into task-oriented, open-domain, and hybrid systems. These systems, especially when dialect-aware, face the added challenge of understanding and adapting to linguistic variations.

**Task-oriented dialogue system:** Task-oriented systems are designed to accomplish specific tasks. They integrate NLU, a dialogue manager, and NLG components. The effectiveness of these systems in handling dialects is pivotal. For instance, [Elmadany et al. 2018a; Joukhadar et al. 2019] study the classification of dialogue acts in Arabic dialect utterances, demonstrating the system's capacity to adapt to dialectal variations. [Al-Ghadhban and Al-Twairish 2020] uses the Artificial Intelligence Markup Language (AIML) [Marietto et al. 2013] to build a chatbot that assists students with academic enquiries in the Saudi Arabic dialect.

**Chit-chat dialogue system:** Chit-chat dialogue systems, also known as open-domain systems, primarily focused on daily chat, handle broader interactions. Botta [Ali and Habash 2016] employs AIML and rule-based systems to manage dialectal variation in Egyptian Arabic, incorporating features like short vowels and consonantal doubling. [Ahmed and Hussein 2020] also use AIML for Kurdish dialogues. Additionally, [Alshareef and Siddiqui 2020] train a Seq2Seq model on a tweet corpus to respond to open-domain Arabic questions.

<sup>14</sup><https://iwslt.org/2022/dialect>; Accessed on 9th January, 2024.

<sup>15</sup><https://iwslt.org/2023/low-resource>; Accessed on 9th January, 2024.

<sup>16</sup><https://iwslt.org/2024/low-resource>; Accessed on 9th January, 2024.

A specialized subset of chit-chat systems are socially-aware dialogue systems, which pay close attention to the influence of social norms and factors. These systems are designed to adhere to the cultural and social norms prevalent in different societies [Hovy and Yang 2021]. In different cultures, social norms will no doubt incorporate social dialect, including whatever discourse force it may carry. [Ziems et al. 2023] propose a framework to evaluate dialect differences in cross-dialectal English. Besides, [Zhan et al. 2023] propose the first socially-aware dialogue corpus based on Chinese culture and relevant dialectal norms. Social dialect in a dialogue will dramatically affect human's understanding and behaviors towards speakers. [Rajai and Ennasser 2022] summarize existing problems and strategies towards dealing with social dialect in dialogues.

**Hybrid system:** Hybrid systems combine features of both task-oriented and open-domain systems. An example is the system developed by [Ben Elhaj Mabrouk et al. 2021], which answers user queries in various Arabic dialects like Tunisian, Igbo, Yoruba, and Hausa. This chatbot addresses both official FAQs, especially related to COVID-19, and informal chit-chat, responding to questions in the local dialect.

Awareness of social and societal norms of behaviour is particularly important in dialogue systems that serve specific transactional goals, be it to book a doctor's appointment, to ask question about income tax or to make a customer service complaint. Research in interactional sociolinguistics [Gumperz 1982] has, in a rich body of research in different social contexts – such as employment interviews [Roberts 2021] – shown that people interpret communicative intent against their own background expectations of what is 'normal' or 'expected behaviour'. This has the potential to exacerbate inequality (for example, by restricting access to employment), in particular, for underrepresented groups such as migrants.

In the case of dialogue systems, a lack of representation of different dialects (e.g., due to the lack of diverse training data) has the potential to cause similar effects: If dialogue systems are not socially aware, and what is communicated does not match users' expectations, communicative intent can be misinterpreted, and underrepresented user groups might become disengage from the system. Indeed, previous research on dialogue systems has confirmed the importance of alignment of system style choices with user needs and preferences [Chaves et al. 2022; Følstad and Brandtzaeg 2020; Li and Mao 2015].

## 7 CONCLUSION & FUTURE DIRECTIONS

Dialects are syntactic and lexical variations of a language, often associated with socially or geographically cohesive groups. This paper summarises NLP approaches for dialects of several languages. The need for NLP approaches focusing on dialects of a language rest on four motivations: dialects pose linguistic challenges, benchmarks may not have sufficient dialectic representation, dialect-awareness is important for fair NLP technology, and there has been growing recent work in this direction. The survey identified trends in terms of tasks (which shows shifting focus from dialect classification), languages (with more work in Arabic as compared to other languages) and shifting trend towards mitigation (by either making models dialect-invariant or dialect-aware). Following that, we describe different methods to create dialectic lexicons and datasets, ranging from location/keyword-based filtering to manual (via recruitment of native speakers) and automatic (via automatic perturbation). We then view past work in the context of NLU and NLG.

For NLU, we covered dialect identification, sentiment analysis, morphosyntactic analysis, parsing and more recent work in NLU benchmarks. We described how the availability of datasets in multiple languages has fuelled research in dialect identification which continues to date. Sentiment analysis techniques for dialects included peculiar de-biasing approaches, in addition to dialect invariance and dialect awareness. Approaches to parse dialectic datasets used or adapted existing parsers or develop dialect-specific parsers. Finally, we described how recent work on NLU benchmarks highlight how

adversarial learning and LoRA can be used to reduce the degradation in the performance of dialectic datasets as compared to the standard ones.

In the case of NLG, we described work in summarisation, machine translation and dialogue systems. We described the limited, recent work in multi-document summarisation of dialectic documents. Following that, we discussed approaches for machine translation in the context of dialect normalisation and dialect pivoting depending on whether the translation is between dialects of a language or between dialects and another language. Finally, we described dialogue systems in the context of task-oriented, chat-chat and hybrid systems.

Based on our survey, we now identify future directions and social/ethical implications. We hope that the former will be helpful for NLP research for dialects, while the latter will get more researchers interested in this richly investigated yet emergent area of NLP. We believe that NLP researchers should adopt a socio-technical perspective [Johnson and Verdicchio 2017] on their role and consider not only their own possible biases influencing the selection of training data, the design of algorithms *etc.* but also other social arrangements (*e.g.*, users and their behaviours) relevant to specific systems.

## 7.1 Implications to NLP research

In addition to the trends reported earlier in the paper, the following would be potential future directions in the context of NLP.

*7.1.1 Focusing on unexplored dialects of languages.* : NLP for dialects face problems akin to low-resource languages, in terms of the availability of existing resources and tools. While some dialect families, such as English and Arabic, have seen consistent efforts, dialects for other languages need more focused large-scale efforts for data curation and annotation. While English is arguably the leading language for advances in NLP, efforts remain to be done to fully represent the full diversity of the English language itself through appropriate datasets and models that are curated for specific dialectic tasks. It is not always necessary to create new datasets, given that datasets specific to particular dialects are already available. However, caution is advised for dialogue systems as many existing corpora – with the exception of those focusing on English as a lingua franca (ELF) – are dominated by written texts which may not represent the richness of dialectic variation of spoken language.

*7.1.2 Rethinking the pre-training of LLMs.* : [Chow and Bond 2022] who present a computational grammar for Singaporean English. Such dialectic representations can be useful to generalise the ability of LLMs. It would be beneficial for LLMs to be able to ingest other kinds of information such as dialect-specific grammatical structures. Ability to pre-train LLMs using data in different formats (not just modality, which is currently a popular paradigm) may improve their performance for diverse datasets such as dialects.

*7.1.3 Dialect identification as an auxiliary task.* : Multi-task learning is used to train models for multiple tasks. Dialect identification could be used as one of the tasks in order to train equitable models. [Lent et al. 2023] present a multi-task, multi-lingual dataset of creole languages. They report the baseline performance of NLU and MT tasks on the dataset using appropriate models. Availability of such large benchmarks will aid the development of new methods and models.

*7.1.4 Rethinking LLM Evaluation.* : [Xiao et al. 2023] show hypernetworks for LoRA, they say: “a comprehensive examination of PEFT modules for dialects is needed, which we leave for future work”. Similar evaluations can be performed for other NLP approaches. In addition, new evaluation techniques and metrics will be useful to measure dialectic variation and its potential correlation with the performance of NLP tasks. Two recent papers can be of value. [Lameli and Schönberg 2023]

present a measure for spatial language variation. Using distance between locations as a heuristic for dialectic similarity, they examine variations in dialects of German. Also, [Keleg et al. 2023] use a dataset in Arabic labeled with the degree of dialectness, to train a BERT-based regression model.

*7.1.5 Other Emerging Paradigms.* A recent advancement in dialect identification is early guessing [Kanjirangat et al. 2022]. The approach detects a dialect for incremental input. To evaluate, a sentence is truncated in fragments, and dialect is detected for each fragment. The goal is to identify how much is required to detect a dialect. Similarly, other technologies can be used to aid NLP for dialects. [Berzak et al. 2017] predict native language of a person based on eye gaze data. Since eye-tracking is not as prevalent in accessible technologies, we consider this a frontier in dialect-aware NLP. Finally, LLMs themselves can be used to create dialectic lexicons and datasets. For example, [Artemova and Plank 2023] present an approach for German dialect lexicon induction with LLMs.

## 7.2 Ethical & Social Implications

Overall, dialectic NLP presents an excellent avenue for research with huge social implications. We highlight three considerations of relevance.

*7.2.1 Social Implications.* While everyone speaks a standard dialect, most people tend to feel familiarity with people who speak specific dialects. Furthermore, certain traditions and practices are tied to localities which are in turn tied to dialects. If the goal of NLP research is to make communication seamless then the only correct way to do so is via a strong emphasis on dialects. There is also a growing concern among speakers of specific dialects that their language is dying due to the pervasiveness of English via the internet. As NLP researchers, we should acknowledge these concerns and make headway into preserving as many dialects as possible, at the risk of losing valuable aspects of the vast tapestry of culture and history.

*7.2.2 Dialectic Research By Dialect Speakers.* Linguistic research colonization is the process where researchers who do not speak specific languages nor have connections with them conduct research on said languages. Despite the negative connotation of colonization, this is not a bad thing, because no one should monopolize working on specific languages. However, it highlights that there are haves and have-nots, where the haves are researchers and organizations with funding who can work on dialects and the have-nots are the researchers who would like to work on dialects but simply lack funding. Recently, there has been a growing trend where language speakers are reclaiming dominion over research involving their own languages. For example, there has been an explosive growth in the number of researchers and groups like DeepLearning Indaba, Masakhane from African countries working solely on African languages and organizations like AI4Bharat in India working on Indian languages. Indeed, they have shown that dedicated focus on language research by speakers of these languages lead to better NLP systems. We therefore propose that the organizations with funding leverage their privilege and support those without funding so as to ensure that work on dialects is led and owned by groups that are most connected and impacted by dialects. This will lead to true diversity, equality and inclusivity in NLP research which will strongly impact society.

*7.2.3 Normalizing Working on and Speaking Dialects.* One aspect which limits dialectic research is the concept of shame in speaking a certain language or a dialect, an aspect which is also known as linguistic self-hatred<sup>1718</sup>. For example, take the case of Mauritian creole, whose speakers are

<sup>17</sup><https://unravellingmag.com/articles/linguistic-self-hate/>; Accessed on 9th January, 2024.

<sup>18</sup><https://languagehat.com/linguistic-self-hatred/>; Accessed on 9th January, 2024.



dwindling by the day, mainly because the younger generation feels shame<sup>19</sup> in speaking their native language. The same exists for Konkani<sup>20</sup>. While there are no official reports highlighting the same for dialects, it is not farfetched to consider that linguistic self-hatred will exist here as well. It is time to end this self-hatred and normalize speaking dialects. By doing so, people speaking dialects will become more enthusiastic about preserving their dialects and this will inevitably aid research on dialects, thereby positively impacting society. Dialects are closely tied to culture and such differences have not been captured explicitly beyond the works described in this paper.

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<sup>19</sup><https://lexpress.mu/blog/286734/creole-disillusion>; Accessed on 11th December 2023.

<sup>20</sup><https://hanvkonn.wordpress.com/2019/06/22/ashamed-of-speaking-in-konkani/>; Accessed on 11th December 2023

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