A survey of diversity quantification in natural language processing: The why, what, where and how

Louis Estève

Marie-Catherine de Marneffe

Nurit Melnik

France Belgium Université Paris-Saclay, CNRS, LISN* FNRS - UCLouvain[†]

Israel
The Open University of Israel[‡]

Agata Savary

France

Université Paris-Saclay, CNRS, LISN*

Abstract

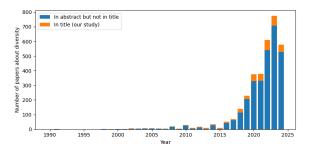
The concept of diversity has received increased consideration in Natural Language Processing (NLP) in recent years. This is due to various motivations like promoting equity and inclusion, approximating human linguistic behavior, and increasing systems' performance. Diversity has however often been addressed in an ad hoc manner in NLP, and with few explicit links to other domains where this notion is better theorized. We survey articles in the ACL Anthology from the past 6 years, with "diversity" or "diverse" in their title. We find a wide range of settings in which diversity is quantified, often highly specialized and using inconsistent terminology. We put forward a unified taxonomy of why, what on, where, and how diversity is measured in NLP. Diversity measures are cast upon a unified framework from ecology and economy (Stirling, 2007) with 3 dimensions of diversity: variety, balance and disparity. We discuss the trends which emerge due to this systematized approach. We believe that this study paves the way towards a better formalization of diversity in NLP, which should bring a better understanding of this notion and a better comparability between various approaches.

1 Introduction

The notion of diversity has been gaining increasing attention in natural language processing (NLP) over the past few years. The top panel of Figure 1 depicts the number of papers in the ACL Anthology from 1990 to 2024-07-26¹ which contain "diversity" or "diverse" in their title or abstract.² There

Olha Kanishcheva

Germany Heidelberg University[§]



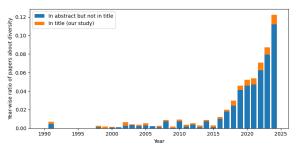


Figure 1: Papers in the ACL Anthology from 1990 until 2024-07-26 with "diversity" or "diverse" in their title or abstract. Top are the raw numbers, bottom the ratio to all papers from the same year in the ACL Anthology.

are 3,653 such papers in total, 3 411 of them contain one of these terms in their title (in orange in Figure 1), and 3,242 in their abstract but not in their title (in blue). Since 2019, these figures amount to 3,162 (total), 308 (title) and 2,854 (abstract). This effect is not only related to the rapid growth of NLP in general. The bottom panel of Figure 1 shows the ratio of the same papers to all papers in the ACL Anthology from the same year. In particular, in the first half of 2024, as many as 12% of all ACL Anthology papers contained the term "diverse" or "diversity" in their title or abstract. These works, however, display disparate understanding of the notion of diversity, as well as a lack of a unified vocabulary and framework needed to evaluate and compare approaches. Even if attempts were made to systematize the notion of diversity in NLP, they

first.last@universite-paris-saclay.fr
marie-catherine.demarneffe@uclouvain.be
huritme@openu.ac.il

kanichshevaolga@gmail.com

¹The date when we downloaded the papers for this survey. ²Prior to 1990, the only one such item is an erratum entitled

²Prior to 1990, the only one such item is an erratum enti Diverse corrigenda and addenda to the pre-prints.

³As a reference, on 2024-07-26, the ACL Anthology contained 97,446 papers.

were limited to particular areas (Tevet and Berant, 2021) or diversity aspects (Ploeger et al., 2024). This suggests that NLP belongs to the "fields [...] where diversity is prominent in discussion, but remains undefined or analytically neglected" (Stirling, 2007, p. 707). The objective of this survey is to take steps towards bridging this gap by taking inspiration from fields where diversity has been theorized and systematically analysed, most prominently ecology. We are particularly interested in systematizing and gaining a better understanding of diversity *quantification* in NLP. Our contributions are twofold:

- a systematic review of the 308 papers from the past 6 years containing "diverse" or "diversity" in their title, from the point of view of diversity quantification,
- a taxonomy allowing to position various approaches with respect to: the motivations behind the quest for diversity (*why*), the objects on which diversity is quantified (*what*), the pipeline stages where diversity measures are applied (*where*) and finally the types of diversity measures themselves (*how*).

2 The theory of diversity

In ecological research, theorizing diversity has seen substantial progress since mentions of diversity by Darwin (1871). Dozens of diversity measures have been defined (Smith and Wilson, 1996) and applied to studies of various species and their habitats. This field borrowed extensively from information theory, through its use of parameterized entropies (Patil and Taillie, 1982) and related transformations (Hill, 1973). Distance measures underlying diversity were addressed for both functional differences (body features, behavior, etc.) and positions in the phylogenetic tree (Mouchet et al., 2010). Several initiatives were undertaken to represent various diversity measures in unified frameworks, mostly based on information theory (Leinster and Cobbold, 2012; Scheiner, 2012; Chao et al., 2014). Properties of various measures have been defined and debated over (Smith and Wilson, 1996; Hoffmann and Hoffmann, 2008; Jost, 2009). As a result, diversity theory in ecology is a rather mature and formalized topic with a substantial bibliography. Inspired by, or parallel to, ecology, various scientific domains such as economics, physics, political science, and linguistics have been concerned with diversity measurement. A unifying framework proposed by for these domain-specific considerations supposes that a system's elements (also called options or items) can be assigned to categories (also called types), e.g. in ecology, categories are often species and elements are specimens. Diversity measures can then be positioned along three dimensions: variety, which focuses on the number of categories, balance, which considers the evenness of the distribution of elements in categories, and disparity, which targets the extent of the differences between categories (Stirling, 1994a,b, 2007; Ramaciotti Morales et al., 2021). For instance, a habitat with 20 species has a higher variety, and therefore a higher diversity, than one with 10 species (whatever their numbers of specimens and differences between them). A habitat hosting 3 species with 100 specimens each is more balanced, and therefore more diverse, than one hosting 3 species with 150, 100, and 50 specimens each. Finally, a habitat with 5 bird species and 5 insect species has a higher disparity than one with 10 insect species. Measures may tackle one or more dimensions at once, as we will see in Section 7. In this survey, we attempt to cast the diversity measures found in NLP to these dimensions. The aim is to introduce a unified vocabulary and taxonomy, make these measures more easily comparable, and assess their applicability beyond the precise contexts in which they were defined.

3 Data and methodology

To explore how diversity is measured in NLP, we conducted a systematic analysis of a subset of papers from the ACL Anthology⁴ that include the terms "diverse" or "diversity" in their title. Specifically, the data for our study consists of papers from the ACL Anthology up to July 26, 2024, which, at that time, hosted 97,466 papers. We focused on papers from the last 5 years (from 2019 to July 26, 2024) that contain the terms "diversity" or "diverse" in their title. While we considered including papers where these terms appear in the abstract, doing so would have significantly increased the number of articles (see Figure 1), making a thorough manual evaluation infeasible. This selection process resulted in 308 articles, which were manually analyzed. We filtered out 39 irrelevant papers.⁵ The

⁴https://aclanthology.org/

⁵Papers judged irrelevant are those which: (i) are not written in English, (ii) speak of non-linguistic diversity (e.g. biodiversity, neurodiversity), (iii) contain "diversity" in their title

	Ethical	Practical	
Goal	inclusiveness, equality, fairness	user expectation, naturalness	
Means	deontology, best practices	performance, informativeness	

Table 1: Motivations behind the quest for diversity.

remaining 269 papers, 197 of which quantify diversity, were annotated to analyze key aspects of how diversity is addressed within NLP research. Our analysis focused on answering four main questions: why diversity is important (Section 4), what aspects of diversity are being measured (Section 5), where within the research pipeline diversity is quantified (Section 6), and how this quantification is performed (Section 7). Seven researchers participated in the annotation. To ensure annotation quality, a partial cross-check was conducted on 93 papers. A thorough analysis of the why, what, where and how dimensions made emerge a taxonomy which we discuss in the following sections.

4 Why diversity is important in NLP

The rapid progress in language technology brought about new opportunities, but also new challenges and requirements. One of them is diversity. It is assumed that diversity is important in many tasks, and that increasing it is desirable. Conversely, its decline, e.g. due to training on synthetic data (Guo et al., 2024), is a concern. The motivations of this quest for diversity, when explicit, can be positioned along two orthogonal dimensions: ethics vs. practicality, and means vs. goal (Table 1). Firstly, language diversity can be seen as a goal in itself, to be pursued for socially ethical reasons. Thus, NLP should promote digital inclusiveness (Joshi et al., 2020). Datasets, systems, and benchmarks are expected to equally serve all users (Khanuja et al., 2023; Liu et al., 2024a), by representing different languages, language families and scripts (Kodner et al., 2022; Goldman et al., 2023) and mitigating the supremacy of English and English-centric bias (Pouran Ben Veyseh et al., 2022; Asai et al., 2022). They should also *fairly* account for diverse cultures (Yin et al., 2021; Mohamed et al., 2022; Keleg and

only because they cite the name of a workshop/shared task or are volumes, (iv) are slides not papers, (v) contain "diversity" only in the title and never in the body of the paper, (vi) describe projects, shared tasks or event/thesis proposals.

Magdy, 2023; Bhatia and Shwartz, 2023; Liu et al., 2024a), human perspectives (Parrish et al., 2024) and opinions (Zhang et al., 2024b). When used in education, they should cover a large variety of topics (Hadifar et al., 2023). Secondly, diversity is used as a means of achieving ethical goals related to deontology and best practices in NLP. Thus, fine-tuning a pre-trained language model with diverse prompts and responses limits the toxic and offensive content in LLM answers (Song et al., 2024). More diverse attention vectors in a transformer make it less sensitive to adversarial attacks, which try to fool it, e.g. to misclassify sentiment or toxicity of a text (Yang et al., 2024). A more diverse benchmark makes evaluation more reliable (Chen et al., 2023b), notably because it shows the out-of-domain performance of a system (Pradhan et al., 2022). As a result, the remaining challenges in NLP are better highlighted (Kim et al., 2023c). Moreover, a dataset's diversity proves more critical in evaluation than its size (Miao et al., 2020). Thirdly, diversity is pursued as a goal for practical reasons likely because, as an inherent property of human language, it has become a user expectation also towards machine-generated language. Thus, generative models should now operate in one-tomany scenarios, i.e. produce a diverse spectrum of outputs (Kumar et al., 2019; Liu et al., 2020; Han et al., 2021; Shao et al., 2022; Puranik et al., 2023; E et al., 2023; Hwang et al., 2023) rather than a single most optimal output. Particularly high diversity expectations are encountered in the domain of dialog (Lee et al., 2022), where more diverse system's reactions increase user's engagement (Akasaki and Kaji, 2019; Kim et al., 2023a). Diversity of human language is considered by some authors as the upper bound of what could be expected from a system, i.e. it should approximate the naturalness of machine-generated text (Schüz et al., 2021; Cegin et al., 2023; Liu et al., 2024b). Finally, in numerous cases diversity is a means to achieve practical benefits, most notably performance. For instance, higher diversity of training data has positive impact on performance in parsing (Narayan and Cohen, 2015; Liu and Zeldes, 2023), question answering (Yang et al., 2018; Yadav et al., 2024), semantic role labeling (Tripodi et al., 2021), solving math problems (Shen et al., 2022), natural language generation (Li et al., 2016; Agirre et al., 2016; Zhu et al., 2018; Zhang et al., 2021; Thompson and Post, 2020; Palumbo et al., 2020; Li et al., 2021), etc. An ensemble model built of diverse submodels has better performances than a unique model (Song et al., 2021; Kobayashi et al., 2022). Extending class names with diverse semantically close keywords increases the accuracy of classification (Yano et al., 2024). One of the reasons of this positive impact of diversity on performances is a better coverage and representativeness of domains, tasks, genres, hallucinations types (Xia et al., 2024), etc. Another practical effect of diversity is informativeness: more diverse generated text is less generic and more informative for users (Park et al., 2023). The quest for diversity, notably in generation, is counterbalanced by the potential difficulty to pursue simultaneously maintaining generative quality and consistence (Ma et al., 2024). This is called the quality/diversity trade-off (Ippolito et al., 2019; Zhang et al., 2021; Shao et al., 2022), or faithfulness-diversity tradeoff (Chen et al., 2023a). While most of these works advocate for an increase of diversity, others posit that it should be adjusted to each task (Liu et al., 2024c). For instance, answers to factual questions call for precision and determinism (low diversity), while storytelling requires creativity and surprise (high diversity). Finally, a high diversity of generated text and its closeness to the diversity of human production, might not be an objective per se. For instance, the difference in diversity patterns between human-generated and AI-generated text may be an opportunity to effectively distinguish these two categories. This notably serves bot detection on social media, avoidance of fake news and protection of democracy (Kosmajac and Keselj, 2019). One final reason for the interest in diversity is to theorize it, and systematize its measurement, so as to understand better its nature and implications (Ploeger et al., 2024), make educated choices of diversity measures (Tevet and Berant, 2021; Lion-Bouton et al., 2022), and offer a reliable comparative framework for NLP (Poelman et al., 2024). Our work falls precisely within this motivation.

5 What diversity is measured on

The papers in our database address a wide range of "diversities" across NLP areas, pursue different goals and utilize varying terminologies (see Section 4). However, by applying the unified conceptual framework from Section 2, we categorize these approaches into 3 broad types: *in-text diversity*, for which categories are linguistic properties

(e.g. vocabulary or semantics); *meta-linguistic diversity*, where categories are classifications of texts in datasets (e.g. their languages or domains); and *diversity of processing*, for which categories relate to methods and processes (e.g. models or tasks). Note that a paper can account for more than one broad type.

5.1 In-text diversity

In-text diversity involves categories which are associated with linguistic properties that are implicitly assumed to be inherent to a text, whether it is written, spoken, or signed. It is addressed and quantified in 124 papers (out of 198) in our dataset. For example, Guo et al. (2024) find that through successive iterations, synthetic texts exhibit a consistent decrease in their lexical, semantic and syntactic diversity. Lexical diversity is operationalized in their system with (i) tokens of words as elements and unique words as categories and (ii) n-grams as elements and unique n-grams as categories. Semantic and syntactic diversity in their approach can be understood as disparity, with sentences being both categories and elements. Similarly, sets of LMgenerated responses (Gao et al., 2019; Tevet and Berant, 2021; Han et al., 2022), captions (Schüz et al., 2021), translations (Burchell et al., 2022; Shao et al., 2022; Wu et al., 2020), paraphrases (Kumar et al., 2019; Bawden et al., 2020; Cao and Wan, 2020) are evaluated with respect to the diversity of the words or word sequences that they contain, as well as the diversity of their semantic contents and syntactic structures.

5.2 Meta-linguistic diversity

Meta-linguistic diversity relates not to texts themselves, but rather to the classifications of texts within datasets. This type of diversity is found in 55 papers. Multilingual datasets are often evaluated with regard to the languages they contain. In the simplest case, languages are both elements and categories. Diversity is characterized by variety - the number of languages - and disparity - the distinctive typological or phylogenetic properties of each language (Pouran Ben Veyseh et al., 2022; Sarti et al., 2022). In a more nuanced characterization of typological diversity, languages are classified according to language families and, sometimes, branches within them (Longpre et al., 2021; Kodner et al., 2022; Kumar et al., 2022a). In our terminology, the languages in that case are the elements and the language branches or families, the categories. However, although the term 'typological diversity' is often evoked, there is a real need for adopting a systematic approach for measuring and comparing it (Ponti et al., 2019; Poelman et al., 2024). Languages are *categories* for Dunn et al. (2020), who draw on the meta-linguistic diversity of Twitter data as a means for understanding the linguistic landscape of countries. With tweets as *elements* categorized into the languages in which they were produced, the authors measure for each country its linguistic diversity over time, and in particular the effect of travel restrictions caused by COVID-19. Other text classifications evaluated with regard to diversity are genres (Liu and Zeldes, 2023), domains or time periods to which the texts belong (Bhattacharyya et al., 2023). In such cases, the elements are linguistic items, mostly tokens, and the categories are the meta-linguistic categories they belong to. There are also papers that target the diversity of text producers, e.g. the racial identity of language signers (Gueuwou et al., 2023) or the political opinions of authors (Zhang et al., 2024b).

5.3 Diversity of processing

A third type of diversity, addressed only in 24 papers, regards not the data itself, but rather categories associated with the processes that are applied to the data. Thus, unlike the two previous classes, diversity of processing is external to the text itself. This is a wide class; we find diversity ascribed to annotations (Weerasooriya et al., 2023) and annotators (Parrish et al., 2024; Creanga and Dinu, 2024), to the (ensemble of) models used for training (Greco et al., 2022; Kobayashi et al., 2022), to the types of tasks performed (Qiu et al., 2021; Zhang et al., 2024a) and to the attention vectors in the internal design of a model (Huang et al., 2019; Yang et al., 2024). In most of these cases there is no higher-order classifications; "diverse" is conceptualized as "several substantially different" and categories are elements. One exception is Yang and Wan (2022), who investigate metric diversity for long document summarization: the elements here are evaluation metrics (e.g. BLEU, ROUGE, SPICE) which are classified into *categories* (e.g. translation, summarization, semantics).

6 Where diversity is measured

We analyzed where diversity is quantified in two ways. To have a broad overview of whether some subfields are more concerned with diversity than others, we annotate each paper with its NLP area. We also determined at which stage of a standard NLP pipeline quantification happens.

6.1 NLP areas

We annotated each paper in our database according to the main NLP area the study targets, identifying 21, as shown in Table 2. Given the recent uptake in NLP for generating data, it is not surprising that Generation is the most frequent area (61 papers, thus 31% of the 197 papers surveyed in which diversity is quantified). All papers in that area aim at generating outputs that are "diverse" (mostly in terms of in-text diversity, Section 5.1). This also holds for the areas of Dialogue, Machine translation, Paraphrasing, Question answering and Summarisation, in which text is often generated. Corpus creation is also an area in which diversity, mostly metalinguistic diversity (Section 5.2), is prominently used (22 papers, thus 11% of the total number of papers). Concerns about diversity are also apparent in *Classification* tasks. Other tasks in the survey on a smaller scale include Modeling, Recommendation, Parsing, Evaluation, Information extraction, Morphology, Vision, Inference, Language Technology, Speech, Survey/Opinion pieces, Matching and Spellchecking.

NLP area	
Generation	
Corpus creation	22
Classification	
Dialogue	
Machine translation / Paraphrasing	
Question answering / Summarization	
Modeling	
Recommendation / Parsing	
Evaluation / Information extraction / Lan-	
guage Technology	
Morphology / Vision / Inference	
Speech / Survey or Opinion paper	
Matching / Spellchecking	

Table 2: Number of papers per NLP area of the paper (areas with the same number of papers are on one line).

6.2 Pipeline stages

Figure 2 shows the different stages of a standard NLP pipeline, detailed here.

Data collection Different methods or criteria are used to select data with diversity in mind. *Elements* are thus methods/criteria and *categories* are groupings of these. Kim et al. (2023c) focus on math word problems and create a more diverse dataset than previously existing ones, in terms of problem types (arithmetic, correspondence, comparison, geometry, possibility), lexical usage (as measured by a lexical diversity measure), languages (they include both English and Korean), and intermediate solution forms (different equation templates).

Annotation process The annotation is done with diverse pools of annotators (human or machine). *Elements* are the annotators, *categories* are some annotator properties (e.g. perspective, sociodemographics). In NLI for example, Creanga and Dinu (2024) consider the diversity of human annotators, with annotators as *elements* and perspectives as *categories*, where diversity pertains thus to processing (Section 5.3). The potential benefits of such an approach is to better represent different worldviews, and consequently improve system performance.

Input data The data given to the system is diverse. *Elements* are typically occurrences of linguistic entities and *categories* are groupings of these elements (e.g. token per lemma, document per genre, tweet per geolocation). An example is Liu and Zeldes (2023) who show that the metalinguistic diversity (Section 5.2) of training sets positively impacts the performance of downstream discourse parsing. Diversity is operationalized with respect to the number of genres that the training sets cover (e.g. academic, bio, interview) and the number of discourse units within each genre.

System construction The process itself is diversity-driven. For instance, in a standard machine learning process, the loss function can be a diversity measure. Yang et al. (2024) assume that if a transformer-based model has diverse patterns in its attention layers, it is less sensitive to attacks by adversarial examples. Thus, while training the model, the loss function is defined as the volume of the geometry formed by attention vectors, and maximization of this volume is sought. Here, attention vectors are *elements* and their own *categories*.

Output data System's output is measured for diversity. For instance, Han et al. (2022) propose a semantic diversity measure of generated answers, which correlates better with human judgements on

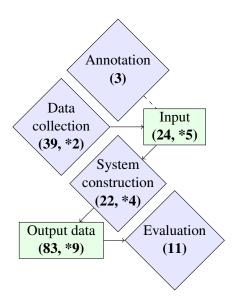


Figure 2: High-level stages in NLP pipelines (diamonds for processes, rectangles for states). Numbers in parentheses are how many papers quantify diversity. Starred * numbers indicate papers with two-stage quantification.

answer diversity. *Elements* are response instances, and *categories* semantic clusters.

Evaluation Different metrics/criteria are used to evaluate systems' outputs, for instance to reinforce their applicability. In other words, *elements* are metrics/criteria and *categories* are groupings of these. This falls under diversity of processing (Section 5.3). For instance, in Yang and Wan (2022), summaries are evaluated with task-specific metrics – translation (BLEU, NIST), summarization (ROUGE), image captioning (ROUGE/CIDEr, SPICE), semantics (BERTScore, Meteor) – to find which measures output the same summary rankings. Thus, as mentioned in Section 5.3, the *elements* are the metrics, and the *categories* the NLP tasks in which these metrics are used.

In which stage(s) is diversity quantified? For each of the 198 papers in which diversity is quantified, we identified the stage(s) in which the quantification of diversity occurs. 192 papers fit the pipeline (some *Opinion* and *Language Technology* papers did not). Each pipeline stage in Figure 2 gives the number of papers in which diversity is quantified in that stage (starred * numbers indicate papers in which quantification happens in two stages). As *Generation* is the most frequent NLP area in our dataset, "Output data" is unsurprisingly the stage in which diversity is most often quantified (83 out of 197 papers): 46 of these are from the *Generation* area, 9 from *Dialogue*, 6 from *Para-*

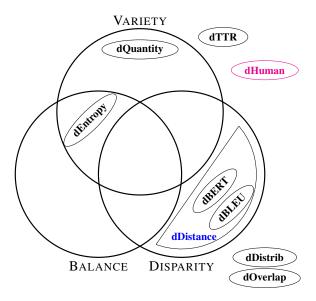


Figure 3: Casting measurement families onto the three dimensions of diversity.

phrasing and 5 from Machine translation. The "Data collection" stage is also prominently featured, with 13 of the 39 papers belonging to the Corpus creation area. In 10 papers, diversity is measured in two stages. For 4 papers, quantification happens at Input & Output data; for 3, at System construction & Output data; for 2, at Data collection & Output data; and in 1, at Input data & System construction.

7 How diversity is measured

Looking at all 197 papers with actual quantification of diversity, we found 150 different diversity measures. Most are used in a handful of papers, thus most papers are not comparable to each other. The individual measures can however be apportioned into families, as many are variant of one another, or have similar mechanisms. The families are presented in Table 3, by decreasing number of papers using measures from said families. The families are further cast on the 3 dimensions of diversity (Section 2) in the Venn's diagram in Fig. 3.

While we cannot present each individual measure we here sketch an emblematic measure per family. Henceforth, the set for which diversity is measured will be called the *observed set*, while n and m will denote the number of its categories and elements (called *observed categories* and *observed elements*), respectively. $P = \langle p_1, ..., p_n \rangle$ will denote the array of category frequencies, and $D = \langle \langle d_{1,1}, ..., d_{1,n} \rangle$, ..., $\langle d_{n,1}, ..., d_{n,n} \rangle \rangle$ the matrix of distances between the categories.

7.1 Absolute quantification

Absolute quantification measures assign a score to the observed set independently of other sets. This covers many measures from this survey, which can be divided into the following families.

dQuantity In this family, measures often consist of just richness, which is the number of categories, i.e. the most elementary variety measure:

$$richness(n, m, P, D) = n \tag{1}$$

This measure is used in many papers, especially those quantifying meta-linguistic diversity, e.g. Kodner et al. (2022); Bella et al. (2022); Balachandran et al. (2022); Altinok (2023).

dTTR This family consists of variants of

$${\it type-token-ratio}\,(n,m,P,D) = \frac{n}{m} \ (2)$$

which is the number of categories normalized by dataset size. A frequent variant of TTR is Distinct-n, also called Dist-n or Diverse-n, which is the ratio of distinct n-grams to the total number of tokens, rather than to the number of n-grams (Li et al., 2016), with often $n \in [1,4]$. Distinct-n is widely used, (Yang et al., 2020; Schüz et al., 2021; Dopierre et al., 2021; Liu et al., 2023; Ma et al., 2024; Guo et al., 2024), however it has issues (Bestgen, 2024). Importantly for us, it is not monotonic to the number of categories (e.g. for a constant n, increasing m reduces the score). This questions its status as a variety and places it outside the Venn's diagram.

dEntropy This family tackles variety like dQuantity but also tackles balance. Its main measure is Shannon and Weaver's (1949) entropy, which is the weighted average of the *surprise* $\log_b\left(p_i^{-1}\right)$ of observing a category with index i:

$$\operatorname{entropy}\left(n,m,P,D\right) = \sum_{i=1}^{n} p_{i} \log_{b}\left(p_{i}^{-1}\right) \ (3)$$

This measure is central to information theory. It accounts for variety as its maximum is $\log_b{(n)}$, and it accounts for balance as it increases with evenness. It is used for example by Chubarian et al. (2021); Puranik et al. (2023); Hwang et al. (2023); Park et al. (2023).

dDistance These measures often aggregate the distance matrix and possibly normalize the outcome, therefore they can be cast in disparity. A standard normalized form, which we refer to as pairwise is

$$\text{pairwise} (n, m, P, D) = \frac{2 * \sum\limits_{i=1}^{n} \sum\limits_{j=1}^{i-1} d_{i,j}}{n(n-1)} \quad (4)$$

It is used for example by Kim et al. (2024, eq. 6). This measure takes the sum of the bottom-lefthand corner of the distance matrix – which implies greater diversity the greater it is – and normalizes it by the number of unique pairs of distinct categories.⁶ Aggregation of the distance matrix can also be operationalized by e.g. the volume of the geometry formed by vector vertices (Yang et al., 2024) or entropy of distances (Yu et al., 2022). Other authors who use measures from dDistance include Stasaski and Hearst (2022); Samir and Silfverberg (2023); Kobayashi et al. (2022); Bawden et al. (2020); Kumar et al. (2019). We define specific subsets of dDistance containing measures which use similarity (rather than distance) functions specific to NLP applications: dBLEU and dBERT. Notably, Self-BLEU (Zhu et al., 2018) is the average of BLEU between each pair of sentences. This means the same logic as pairwise in Equation 4, with BLEU as the similarity function (thus, the lower the score the higher the diversity), and n^2 instead of n(n-1)/2 as a denominator. For BERT however, the logic differs, through the use of BERTScore (Zhang* et al., 2020). Considering sentences X and Y, it first computes precision and recall (by aligning tokens):

$$R_{\text{BERT}} = \frac{1}{|X|} \sum_{x_i \in X} \max_{y_j \in Y} \vec{x_i}^\top \vec{y_j}$$
 (5)

$$P_{\text{BERT}} = \frac{1}{|Y|} \sum_{u \in Y} \max_{x_i \in X} \vec{y_j}^{\top} \vec{x_i}$$
 (6)

where x_i and y_j are tokens from X and Y, and $\vec{x_i}$ and $\vec{y_j}$ are their embeddings. Then the F1-score is computed from R_{BERT} and P_{BERT} . Authors using dBLEU include (Shao et al., 2022; Han et al., 2021; Miao et al., 2020) and those using dBERT are e.g. (Puranik et al., 2023; E et al., 2023; Kim et al., 2023a; Cao and Wan, 2020).

7.2 Relative quantification

In the families above, a distance function is used to assess the difference between categories from a single set (the observed set). However, some families use two sets: a reference set R and the observed set O whose diversity is estimated by comparison R. In one version of this scenario, R is considered diverse, e.g. it is curated with diversity in mind, and O should be as close as possible to R (Samardzic et al., 2024). In another version, conversely, O is expected to differ from R, e.g. generated utterances should be different from the training utterances (Murahari et al., 2019). Measures of this type are positioned outside of the Venn's diagram in Figure 3.

dDistrib These measures compare the reference and observed distributions Q and P of R's and O's elements in categories, respectively. One example, used by Kumar et al. (2022b), is

$$\operatorname{cross-entropy}\left(Q,P\right) = \sum_{i=1}^{n} q_{i} \log_{b}\left(p_{i}^{-1}\right)$$

which is the average surprise of observing a category of index i with a reference probability $p_i \in P$ but an observed probability $q_i \in Q$. Such measures are used e.g. by Liu et al. (2024b); Xia et al. (2024).

dOverlap Here, instead of comparing the distributions of the categories in the two sets, we focus on how many categories are shared by these sets. One example is the Jaccard measure

$$\operatorname{Jaccard}(R,O) = \frac{|R \cap O|}{|R \cup O|} \tag{8}$$

This measure consists of the ratio of shared categories between the two sets, and is thus defined on the range [0,1]. Authors using measures from dOverlap include Thompson and Post (2020); Samardzic et al. (2024).

7.3 Introspective quantification

We saw above that diversity is considered inherent to human language. By extension, humans are considered capable to judge diversity in text simply by introspection. One family of measures builds upon this assumption.

dHuman Human experts are presented samples of text which they have to either rank for diversity (Liu et al., 2023) or score along a diversity scale

⁶Note that measures from **dDistance** incur an $O(n^2)$ cost.

(Kim et al., 2023b). We cannot a priori know if humans rely on categories and elements for their judgment, therefore, this family was placed outside of the Venn's diagram in Figure 3.

Several observations can be made about the surveyed diversity measures. Firstly, the most frequent families of measures are dDistance and dQuantity, i.e. pure disparities and pure varieties. Secondly, no family lies solely in balance⁷, and none lies on the cross-roads of disparity with balance and/or variety⁸ The latter observation partly results from the vagueness of the definition of a variety, e.g. it is unclear how far formula (4) "focuses on the number of categories", as required by a variety (Section 2). Thirdly, it happens that two different diversity measures bear the same name. This is the case of Distn, which can either mean the (natural) number of distinct n-grams in a text (Xu et al., 2018), or the same number divided by the total number of words in the text (Li et al., 2016). The first case belongs to dQuantity, i.e. a variety measure, and the second to dTTR, i.e. is not a proper diversity as discussed above.

8 Discussion

As seen above, diversity is a very prevalent concept in NLP. It is measured in many areas, in most stages of NLP pipelines, applied to a wide range of categories, and for many different reasons. However, this state of the art is characterized by informality and cross-paper inconsistency. As many as 72 reviewed papers (out of the 269 relevant ones) consider diversity to be important without defining and quantifying it. In 54 of the 197 papers where quantification is found, it is limited to counting the number of categories (variety), and in some cases a framework covering several categories is already considered diverse. In the other 143 papers, diversity measures are numerous and target different dimensions but there is no uniform terminology and methodology, to the point of calling the same measure different names or using the same name for different measures. What is more, the choice of these measures is rarely justified and their properties are not addressed. We found very few explicit

However,	measures	based	on	Zipfian	parameter	rs (in
dOther) occur	rred twice	(Zhang	g et	al., 2023	3; Hwang	et al.,
2023), account	ing solely	for bala	nce.	•		

⁸Such measures exist in ecology (Ricotta and Szeidl, 2006; Leinster and Cobbold, 2012; Scheiner, 2012; Chao et al., 2014).

Family	#
dQuantity: count categories	55
dBLEU: use BLEU for distances.	41
dDistance: quantify differences be-	37 + 8
tween categories	+ 41
dTTR : use the number of categories	30
and normalize it by the number of ele-	
ments	
dEntropy : calculate unpredictability	21
of categories	
dOverlap: find the overlap between	9
the categories in the observed set and	
in a reference set	
dBERT : use BERT's contextual vec-	8
tor space for distances	
dHuman: rely on a human evaluation	7
dDistrib: use the distance between	3
observed and reference distributions	
dOther: other measures	36

Table 3: Families of diversity measures and number of articles (#) using them. Arguably, dBLEU (blue) and dBERT (green) are sub-families of dDistance.

links to longstanding theories of diversity from domains like ecology. In particular, hardly any papers refer explicitly to variety, balance or disparity, as presented in Section 2. For these reasons, the statistics reported in this survey should not be taken at face value but rather as indications. Namely, it is us, not the papers' authors, who identified the elements and categories, and interpreted the measures in terms of the theory of diversity. In many cases measures were unclear, even after conducting in-depth analysis or consulting the papers where they were first defined. Nevertheless, the survey improved our understanding of global tendencies in the field along the why, what, where and how axes. Our examination of the intersections between these axes revealed two main prototypical, highly distinct, scenarios. The first involves the area of corpus creation. At the data collection pipeline stage, sources are selected with the ethical goal of ensuring inclusiveness and equality and/or as a practical means of ensuring performance. The diversity categories are *meta-linguistic* and measures from the *dQuantity* family (variety) are used. Papers in this scenario range from as simple a quantification as 3 genres in (Etienne et al., 2022) to as many as dozens of languages with 2 levels of categories in (Vylomova et al., 2020). The latter

describes a shared task on morphological inflection in which diversity is operationalized in the choice of languages for the dataset: 90 languages from 34 genera, grouped into 15 language families. Families are used as proxies of different types of morphological systems. The task is to generate inflected forms from a lemma and a set of features. The systems are required to generalize across typologically distinct languages (also those unseen in training) many of which are low-resourced. This shows both ethical and practical motivations for collecting diverse data. The second scenario occurs in generation at the output data stage, where in-text categories are used for evaluation. Diversity is a practical goal related to user expectations or naturalness. Often the *one-to-many* scenario occurs and the quality/diversity trade off has to be balanced. The measures are mostly from the dTTR or dDistance families. For example, Liu et al. (2023) investigate response generation for multiturn dialogue in generative chatbots. Their objective is to enhance chatbot responses for diversity and relevance simultaneously. They use recurrent neural networks (whose basic transition structure is deterministic) into which they introduce a recurrent summarizing latent variable (to enable variability), to address the one-to-many challenge. The diversity of the generated answers is measured with Distinct-1/2 (dTTR) and with ranking-based human evaluations (dHuman). Related to these scenarios, we put forward two conceptualizations of the relationships between diversity and naturalness. In the first scenario, the fact that few languages are well-resourced and many others are not is arguably natural. Diversity-driven data selection is meant to compensate for this fact, so naturalness and diversity are somehow opposed. In the second scenario, conversely, the diversity of human answers is often an upper bound for the systems' generations, so naturalness and diversity are considered positively correlated. Different degrees of naturalness are also observable in the categories and elements to which diversity measures are applied. On the one hand, we find "natural", i.e. (meta-)linguistically meaningful categories such as words, idiomatic expressions, sentences, syntactic trees, genres, language families, typological features, speakers, countries, ethnicities, NLP tasks, etc. On the other hand, "artificial" (i.e. non-linguistic) categories are observed, such as n-grams, BERT word pieces, word embeddings, attention vectors, or points in a vector space.

Those approximate more natural categories (whose diversity might be too hard to compute). Let us finally notice the relatively high frequency (74 papers) of cases when diversity measures are applied directly to elements, without apportionment into categories. This happens most often when utterances on input or output of the system are compared by similarity measures like Self-BLEU or BERT-score. Such scenarios can be seen as trivial cases of disparity measurement in which elements are identical to categories. Variety is then roughly equivalent to dataset size (and not considered as a diversity dimension) and balance is moot. Such cases reveal the tension between NLP, where continuous representations are prevalent, and domains like ecology, in which categorical modeling is standard. This tension might be a reason why theoretical diversity, based on categorization, has little popularity in NLP so far.

9 Conclusions and future work

The use of "diverse" and "diversity" in NLP research has increased significantly, despite the lack of a formalized definition. To analyze how diversity is measured, we conducted a survey of ACL Anthology papers (2019-01-01 through 2024-07-26), examining why, what, where, and how diversity is quantified. Our study introduces taxonomies that capture key trends in diversity measurement. Diversity is primarily measured under three perspectives: in-text diversity (most common), meta-linguistic diversity, and diversity of processing. While diverse NLP areas address these aspects, generation focuses on in-text diversity, whereas corpus creation emphasizes meta-linguistic diversity. The most frequent pipeline stages where diversity is quantified are output data and data collection. We identified 150 distinct diversity measures, which often emphasize variety (number of categories) and disparity (differences between categories), but rarely balance. Some measures may be cast into the formal framework used in ecology, but many remain NLP-specific. Based on our results, we recommend standardizing diversity quantification in NLP and systematically incorporating diversity as an evaluation criterion in benchmarks. Future research should systematize and further enhance methods for achieving diversity, such as sampling strategies and model training techniques.

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References

Eneko Agirre, Carmen Banea, Daniel Cer, Mona Diab, Aitor Gonzalez-Agirre, Rada Mihalcea, German Rigau, and Janyce Wiebe. 2016. SemEval-2016 task 1: Semantic textual similarity, monolingual and cross-lingual evaluation. In *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, pages 497–511, San Diego, California. Association for Computational Linguistics.

Satoshi Akasaki and Nobuhiro Kaji. 2019. Conversation initiation by diverse news contents introduction. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 3988–3998, Minneapolis, Minnesota. Association for Computational Linguistics.

Duygu Altinok. 2023. A diverse set of freely available linguistic resources for Turkish. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 13739–13750, Toronto, Canada. Association for Computational Linguistics.

Akari Asai, Shayne Longpre, Jungo Kasai, Chia-Hsuan Lee, Rui Zhang, Junjie Hu, Ikuya Yamada, Jonathan H. Clark, and Eunsol Choi. 2022. MIA 2022 shared task: Evaluating cross-lingual open-retrieval question answering for 16 diverse languages. In *Proceedings of the Workshop on Multilingual Information Access (MIA)*, pages 108–120, Seattle, USA. Association for Computational Linguistics.

Vidhisha Balachandran, Hannaneh Hajishirzi, William Cohen, and Yulia Tsvetkov. 2022. Correcting diverse factual errors in abstractive summarization via post-editing and language model

infilling. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 9818–9830, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Rachel Bawden, Biao Zhang, Lisa Yankovskaya, Andre Tättar, and Matt Post. 2020. A study in improving BLEU reference coverage with diverse automatic paraphrasing. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 918–932, Online. Association for Computational Linguistics.

Gábor Bella, Erdenebileg Byambadorj, Yamini Chandrashekar, Khuyagbaatar Batsuren, Danish Cheema, and Fausto Giunchiglia. 2022. Language diversity: Visible to humans, exploitable by machines. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 156–165, Dublin, Ireland. Association for Computational Linguistics.

Yves Bestgen. 2024. Measuring lexical diversity in texts: The twofold length problem. *Language learning*, 74(3):638–671.

Mehar Bhatia and Vered Shwartz. 2023. GD-COMET: A geo-diverse commonsense inference model. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 7993–8001, Singapore. Association for Computational Linguistics.

Pramit Bhattacharyya, Joydeep Mondal, Subhadip Maji, and Arnab Bhattacharya. 2023. VACAS-PATI: A diverse corpus of Bangla literature. In Proceedings of the 13th International Joint Conference on Natural Language Processing and the 3rd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1118–1130, Nusa Dua, Bali. Association for Computational Linguistics.

Laurie Burchell, Alexandra Birch, and Kenneth Heafield. 2022. Exploring diversity in back translation for low-resource machine translation. In *Proceedings of the Third Workshop on Deep Learning for Low-Resource Natural Language Processing*, pages 67–79, Hybrid. Association for Computational Linguistics.

- Yue Cao and Xiaojun Wan. 2020. DivGAN: Towards diverse paraphrase generation via diversified generative adversarial network. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 2411–2421, Online. Association for Computational Linguistics.
- Jan Cegin, Jakub Simko, and Peter Brusilovsky. 2023. ChatGPT to replace crowdsourcing of paraphrases for intent classification: Higher diversity and comparable model robustness. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 1889–1905, Singapore. Association for Computational Linguistics.
- Anne Chao, Chun-Huo Chiu, and Lou Jost. 2014. Unifying Species Diversity, Phylogenetic Diversity, Functional Diversity, and Related Similarity and Differentiation Measures Through Hill Numbers. *Annual Review of Ecology, Evolution, and Systematics*, 45:297–324. Publisher: Annual Reviews.
- Wei-Lin Chen, Cheng-Kuang Wu, Hsin-Hsi Chen, and Chung-Chi Chen. 2023a. Fidelity-enriched contrastive search: Reconciling the faithfulness-diversity trade-off in text generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 843–851, Singapore. Association for Computational Linguistics.
- Yulong Chen, Yang Liu, Ruochen Xu, Ziyi Yang, Chenguang Zhu, Michael Zeng, and Yue Zhang. 2023b. UniSumm and SummZoo: Unified model and diverse benchmark for few-shot summarization. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 12833–12855, Toronto, Canada. Association for Computational Linguistics.
- Karine Chubarian, Abdul Rafae Khan, Anastasios Sidiropoulos, and Jia Xu. 2021. Grouping words with semantic diversity. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3217–3228, Online. Association for Computational Linguistics.
- Claudiu Creanga and Liviu P. Dinu. 2024. Designing NLP systems that adapt to diverse world-

- views. In Proceedings of the 3rd Workshop on Perspectivist Approaches to NLP (NLPerspectives) @ LREC-COLING 2024, pages 95–99, Torino, Italia. ELRA and ICCL.
- Charles Darwin. 1871. *The Descent of Man, and Selection in Relation to Sex*, volume 1. John Murray, Albemarle Street., London. Manual entry.
- Thomas Dopierre, Christophe Gravier, and Wilfried Logerais. 2021. PROTAUGMENT: Unsupervised diverse short-texts paraphrasing for intent detection meta-learning. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 2454–2466, Online. Association for Computational Linguistics.
- Jonathan Dunn, Tom Coupe, and Benjamin Adams. 2020. Measuring linguistic diversity during COVID-19. In *Proceedings of the Fourth Workshop on Natural Language Processing and Computational Social Science*, pages 1–10, Online. Association for Computational Linguistics.
- Venkatesh E, Kaushal Maurya, Deepak Kumar, and Maunendra Sankar Desarkar. 2023. DivHSK: Diverse headline generation using self-attention based keyword selection. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 1879–1891, Toronto, Canada. Association for Computational Linguistics.
- Aline Etienne, Delphine Battistelli, and Gwénolé Lecorvé. 2022. A (psycho-)linguistically motivated scheme for annotating and exploring emotions in a genre-diverse corpus. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 603–612, Marseille, France. European Language Resources Association.
- Xiang Gao, Sungjin Lee, Yizhe Zhang, Chris Brockett, Michel Galley, Jianfeng Gao, and Bill Dolan. 2019. Jointly optimizing diversity and relevance in neural response generation. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers),

- pages 1229–1238, Minneapolis, Minnesota. Association for Computational Linguistics.
- Omer Goldman, Khuyagbaatar Batsuren, Salam Khalifa, Aryaman Arora, Garrett Nicolai, Reut Tsarfaty, and Ekaterina Vylomova. 2023. SIGMORPHON–UniMorph 2023 shared task 0: Typologically diverse morphological inflection. In Proceedings of the 20th SIGMORPHON workshop on Computational Research in Phonetics, Phonology, and Morphology, pages 117–125, Toronto, Canada. Association for Computational Linguistics.
- Claudio Greco, Alberto Testoni, Raffaella Bernardi, and Stella Frank. 2022. A small but informed and diverse model: The case of the multimodal GuessWhat!? guessing game. In *Proceedings of the 2022 CLASP Conference on (Dis)embodiment*, pages 1–10, Gothenburg, Sweden. Association for Computational Linguistics.
- Shester Gueuwou, Sophie Siake, Colin Leong, and Mathias Müller. 2023. JWSign: A highly multilingual corpus of Bible translations for more diversity in sign language processing. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 9907–9927, Singapore. Association for Computational Linguistics.
- Yanzhu Guo, Guokan Shang, Michalis Vazirgiannis, and Chloé Clavel. 2024. The curious decline of linguistic diversity: Training language models on synthetic text. In *Findings of the Association for Computational Linguistics: NAACL 2024*, pages 3589–3604, Mexico City, Mexico. Association for Computational Linguistics.
- Amir Hadifar, Semere Kiros Bitew, Johannes Deleu, Veronique Hoste, Chris Develder, and Thomas Demeester. 2023. Diverse content selection for educational question generation. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics: Student Research Workshop*, pages 123–133, Dubrovnik, Croatia. Association for Computational Linguistics.
- Jiuzhou Han, Daniel Beck, and Trevor Cohn. 2021. Generating diverse descriptions from semantic graphs. In *Proceedings of the 14th International Conference on Natural Language Generation*, pages 1–11, Aberdeen, Scotland, UK. Association for Computational Linguistics.

- Seungju Han, Beomsu Kim, and Buru Chang. 2022. Measuring and improving semantic diversity of dialogue generation. In *Findings of the Association for Computational Linguistics: EMNLP* 2022, pages 934–950, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- M. O. Hill. 1973. Diversity and Evenness: A Unifying Notation and Its Consequences. *Ecology*, 54(2):427–432. Number: 2 Publisher: Ecological Society of America.
- Sönke Hoffmann and Andreas Hoffmann. 2008. Is there a "true" diversity? *Ecological Economics*, 65(2):213–215.
- Po-Yao Huang, Xiaojun Chang, and Alexander Hauptmann. 2019. Multi-head attention with diversity for learning grounded multilingual multimodal representations. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 1461–1467, Hong Kong, China. Association for Computational Linguistics.
- EunJeong Hwang, Veronika Thost, Vered Shwartz, and Tengfei Ma. 2023. Knowledge graph compression enhances diverse commonsense generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 558–572, Singapore. Association for Computational Linguistics.
- Daphne Ippolito, Reno Kriz, João Sedoc, Maria Kustikova, and Chris Callison-Burch. 2019. Comparison of diverse decoding methods from conditional language models. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3752–3762, Florence, Italy. Association for Computational Linguistics.
- Pratik Joshi, Sebastin Santy, Amar Budhiraja, Kalika Bali, and Monojit Choudhury. 2020. The state and fate of linguistic diversity and inclusion in the NLP world. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 6282–6293, Online. Association for Computational Linguistics.

- Lou Jost. 2009. Mismeasuring biological diversity: Response to Hoffmann and Hoffmann (2008). *Ecological Economics*, 68(4):925–928.
- Amr Keleg and Walid Magdy. 2023. DLAMA: A framework for curating culturally diverse facts for probing the knowledge of pretrained language models. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 6245–6266, Toronto, Canada. Association for Computational Linguistics.
- Simran Khanuja, Sebastian Ruder, and Partha Talukdar. 2023. Evaluating the diversity, equity, and inclusion of NLP technology: A case study for Indian languages. In *Findings of the Association for Computational Linguistics: EACL 2023*, pages 1763–1777, Dubrovnik, Croatia. Association for Computational Linguistics.
- Donghyun Kim, Youbin Ahn, Wongyu Kim, Chanhee Lee, Kyungchan Lee, Kyong-Ho Lee, Jeonguk Kim, Donghoon Shin, and Yeonsoo Lee. 2023a. Persona expansion with commonsense knowledge for diverse and consistent response generation. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, pages 1139–1149, Dubrovnik, Croatia. Association for Computational Linguistics.
- Donghyun Kim, Youbin Ahn, Chanhee Lee, Wongyu Kim, Kyong-Ho Lee, Donghoon Shin, and Yeonsoo Lee. 2023b. Concept-based Persona Expansion for Improving Diversity of Persona-Grounded Dialogue. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, pages 3471–3481, Dubrovnik, Croatia. Association for Computational Linguistics.
- Jiwoo Kim, Youngbin Kim, Ilwoong Baek, JinYeong Bak, and Jongwuk Lee. 2023c. It ain't over: A multi-aspect diverse math word problem dataset. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 14984–15011, Singapore. Association for Computational Linguistics.
- Yejin Kim, Scott Rome, Kevin Foley, Mayur Nankani, Rimon Melamed, Javier Morales, Abhay K. Yadav, Maria Peifer, Sardar Hamidian, and H. Howie Huang. 2024. Improving Content Recommendation: Knowledge Graph-Based

- Semantic Contrastive Learning for Diversity and Cold-Start Users. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pages 8743–8755, Torino, Italia, ELRA and ICCL.
- Sosuke Kobayashi, Shun Kiyono, Jun Suzuki, and Kentaro Inui. 2022. Diverse lottery tickets boost ensemble from a single pretrained model. In *Proceedings of BigScience Episode #5 Workshop on Challenges & Perspectives in Creating Large Language Models*, pages 42–50, virtual+Dublin. Association for Computational Linguistics.
- Jordan Kodner, Salam Khalifa, Khuyagbaatar Batsuren, Hossep Dolatian, Ryan Cotterell, Faruk Akkus, Antonios Anastasopoulos, Taras Andrushko, Aryaman Arora, Nona Atanalov, Gábor Bella, Elena Budianskaya, nus Ghanggo Ate, Omer Goldman, David Guriel, Simon Guriel, Silvia Guriel-Agiashvili, Witold Kieraś, Andrew Krizhanovsky, Natalia Krizhanovsky, Igor Marchenko, Magdalena Markowska, Polina Mashkovtseva, Maria Nepomniashchaya, Daria Rodionova, Karina Scheifer, Alexandra Sorova, Anastasia Yemelina, Jeremiah Young, and Ekaterina Vylomova. 2022. SIGMORPHON–UniMorph 2022 shared task 0: Generalization and typologically diverse morphological inflection. In Proceedings of the 19th SIGMORPHON Workshop on Computational Research in Phonetics, Phonology, and Morphology, pages 176-203, Seattle, Washington. Association for Computational Linguistics.
- Dijana Kosmajac and Vlado Keselj. 2019. Twitter bot detection using diversity measures. In *Proceedings of the 3rd International Conference on Natural Language and Speech Processing*, pages 1–8, Trento, Italy. Association for Computational Linguistics.
- Aman Kumar, Himani Shrotriya, Prachi Sahu, Amogh Mishra, Raj Dabre, Ratish Puduppully, Anoop Kunchukuttan, Mitesh M. Khapra, and Pratyush Kumar. 2022a. IndicNLG benchmark: Multilingual datasets for diverse NLG tasks in Indic languages. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 5363–5394, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

- Ashutosh Kumar, Satwik Bhattamishra, Manik Bhandari, and Partha Talukdar. 2019. Submodular optimization-based diverse paraphrasing and its effectiveness in data augmentation. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 3609–3619, Minneapolis, Minnesota. Association for Computational Linguistics.
- Shanu Kumar, Sandipan Dandapat, and Monojit Choudhury. 2022b. "diversity and uncertainty in moderation" are the key to data selection for multilingual few-shot transfer. In *Findings of the Association for Computational Linguistics:* NAACL 2022, pages 1042–1055, Seattle, United States. Association for Computational Linguistics.
- Jing Yang Lee, Kong Aik Lee, and Woon Seng Gan. 2022. A randomized link transformer for diverse open-domain dialogue generation. In *Proceedings of the 4th Workshop on NLP for Conversational AI*, pages 1–11, Dublin, Ireland. Association for Computational Linguistics.
- Tom Leinster and Christina A. Cobbold. 2012. Measuring diversity: the importance of species similarity. *Ecology*, 93(3):477–489.
- Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016. A diversity-promoting objective function for neural conversation models. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 110–119, San Diego, California. Association for Computational Linguistics.
- Junyi Li, Tianyi Tang, Gaole He, Jinhao Jiang, Xiaoxuan Hu, Puzhao Xie, Zhipeng Chen, Zhuohao Yu, Wayne Xin Zhao, and Ji-Rong Wen. 2021. TextBox: A unified, modularized, and extensible framework for text generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing: System Demonstrations*, pages 30–39, Online. Association for Computational Linguistics.

- Adam Lion-Bouton, Yagmur Ozturk, Agata Savary, and Jean-Yves Antoine. 2022. Evaluating diversity of multiword expressions in annotated text. In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 3285–3295, Gyeongju, Republic of Korea. International Committee on Computational Linguistics.
- Chen Liu, Fajri Koto, Timothy Baldwin, and Iryna Gurevych. 2024a. Are multilingual LLMs culturally-diverse reasoners? an investigation into multicultural proverbs and sayings. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 2016–2039, Mexico City, Mexico. Association for Computational Linguistics.
- Dayiheng Liu, Yeyun Gong, Yu Yan, Jie Fu, Bo Shao, Daxin Jiang, Jiancheng Lv, and Nan Duan. 2020. Diverse, controllable, and keyphrase-aware: A corpus and method for news multi-headline generation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6241–6250, Online. Association for Computational Linguistics.
- Guisheng Liu, Yi Li, Zhengcong Fei, Haiyan Fu, Xiangyang Luo, and Yanqing Guo. 2024b. Prefix-diffusion: A lightweight diffusion model for diverse image captioning. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pages 12954–12965, Torino, Italia. ELRA and ICCL.
- Mingyue Liu, Jonathan Frawley, Sarah Wyer, Hubert P. H. Shum, Sara Uckelman, Sue Black, and Chris Willcocks. 2024c. Self-regulated sample diversity in large language models. In *Findings of the Association for Computational Linguistics:* NAACL 2024, pages 1891–1899, Mexico City, Mexico. Association for Computational Linguistics.
- Yang Janet Liu and Amir Zeldes. 2023. Why can't discourse parsing generalize? a thorough investigation of the impact of data diversity. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational*

- *Linguistics*, pages 3112–3130, Dubrovnik, Croatia. Association for Computational Linguistics.
- Yongkang Liu, Shi Feng, Daling Wang, Yifei Zhang, and Hinrich Schütze. 2023. PVGRU: Generating diverse and relevant dialogue responses via pseudo-variational mechanism. In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 3295–3310, Toronto, Canada. Association for Computational Linguistics.
- Shayne Longpre, Yi Lu, and Joachim Daiber. 2021. MKQA: A linguistically diverse benchmark for multilingual open domain question answering. *Transactions of the Association for Computational Linguistics*, 9:1389–1406.
- Yueen Ma, DaFeng Chi, Jingjing Li, Kai Song, Yuzheng Zhuang, and Irwin King. 2024. VOLTA: Improving generative diversity by variational mutual information maximizing autoencoder. In *Findings of the Association for Computational Linguistics: NAACL 2024*, pages 364–378, Mexico City, Mexico. Association for Computational Linguistics.
- Shen-yun Miao, Chao-Chun Liang, and Keh-Yih Su. 2020. A diverse corpus for evaluating and developing English math word problem solvers. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 975–984, Online. Association for Computational Linguistics.
- Youssef Mohamed, Mohamed Abdelfattah, Shyma Alhuwaider, Feifan Li, Xiangliang Zhang, Kenneth Church, and Mohamed Elhoseiny. 2022. ArtELingo: A million emotion annotations of WikiArt with emphasis on diversity over language and culture. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 8770–8785, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Maud A. Mouchet, Sébastien Villéger, Norman W. H. Mason, and David Mouillot. 2010. Functional diversity measures: an overview of their redundancy and their ability to discriminate community assembly rules. *Functional Ecology*, 24(4):867–876.

- Vishvak Murahari, Prithvijit Chattopadhyay, Dhruv Batra, Devi Parikh, and Abhishek Das. 2019. Improving generative visual dialog by answering diverse questions. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 1449–1454, Hong Kong, China. Association for Computational Linguistics.
- Shashi Narayan and Shay B. Cohen. 2015. Diversity in spectral learning for natural language parsing. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1868–1878, Lisbon, Portugal. Association for Computational Linguistics.
- Enrico Palumbo, Andrea Mezzalira, Cristina Marco, Alessandro Manzotti, and Daniele Amberti. 2020. Semantic diversity for natural language understanding evaluation in dialog systems. In *Proceedings of the 28th International Conference on Computational Linguistics: Industry Track*, pages 44–49, Online. International Committee on Computational Linguistics.
- Jun-Hyung Park, Hyuntae Park, Youjin Kang, Eojin Jeon, and SangKeun Lee. 2023. DIVE: Towards descriptive and diverse visual commonsense generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 9677–9695, Singapore. Association for Computational Linguistics.
- Alicia Parrish, Susan Hao, Sarah Laszlo, and Lora Aroyo. 2024. Is a picture of a bird a bird? a mixed-methods approach to understanding diverse human perspectives and ambiguity in machine vision models. In *Proceedings of the 3rd Workshop on Perspectivist Approaches to NLP (NLPerspectives)* @ *LREC-COLING* 2024, pages 1–18, Torino, Italia. ELRA and ICCL.
- G. P. Patil and C. Taillie. 1982. Diversity as a Concept and its Measurement. *Journal of the American Statistical Association*, 77(379):548–561.
 Number: 379 Publisher: [American Statistical Association, Taylor & Francis, Ltd.].
- Esther Ploeger, Wessel Poelman, Miryam de Lhoneux, and Johannes Bjerva. 2024. What is "typological diversity" in NLP? In *Proceedings of the 2024 Conference on Empirical*

- *Methods in Natural Language Processing*, pages 5681–5700, Miami, Florida, USA. Association for Computational Linguistics.
- Wessel Poelman, Esther Ploeger, Miryam de Lhoneux, and Johannes Bjerva. 2024. A call for consistency in reporting typological diversity. In *Proceedings of the 6th Workshop on Research in Computational Linguistic Typology and Multilingual NLP*, pages 75–77, St. Julian's, Malta. Association for Computational Linguistics.
- Edoardo Maria Ponti, Helen O'Horan, Yevgeni Berzak, Ivan Vulić, Roi Reichart, Thierry Poibeau, Ekaterina Shutova, and Anna Korhonen. 2019. Modeling language variation and universals: A survey on typological linguistics for natural language processing. *Computational Linguistics*, 45(3):559–601.
- Amir Pouran Ben Veyseh, Minh Van Nguyen, Franck Dernoncourt, and Thien Nguyen. 2022. MINION: a large-scale and diverse dataset for multilingual event detection. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2286–2299, Seattle, United States. Association for Computational Linguistics.
- Sameer Pradhan, Julia Bonn, Skatje Myers, Kathryn Conger, Tim O'gorman, James Gung, Kristin Wright-bettner, and Martha Palmer. 2022. PropBank comes of Age—Larger, smarter, and more diverse. In *Proceedings of the 11th Joint Conference on Lexical and Computational Semantics*, pages 278–288, Seattle, Washington. Association for Computational Linguistics.
- Vinayak Puranik, Anirban Majumder, and Vineet Chaoji. 2023. PROTEGE: Prompt-based diverse question generation from web articles. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 5449–5463, Singapore. Association for Computational Linguistics.
- Yao Qiu, Jinchao Zhang, and Jie Zhou. 2021. Different strokes for different folks: Investigating appropriate further pre-training approaches for diverse dialogue tasks. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 2318–2327,

- Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Pedro Ramaciotti Morales, Robin Lamarche-Perrin, Raphaël Fournier-S'niehotta, Rémy Poulain, Lionel Tabourier, and Fabien Tarissan. 2021. Measuring diversity in heterogeneous information networks. *Theoretical Computer Science*, 859.
- Carlo Ricotta and Laszlo Szeidl. 2006. Towards a unifying approach to diversity measures: bridging the gap between the Shannon entropy and Rao's quadratic index. *Theoretical Population Biology*, 70(3):237–243. Number: 3.
- Tanja Samardzic, Ximena Gutierrez, Christian Bentz, Steven Moran, and Olga Pelloni. 2024. A measure for transparent comparison of linguistic diversity in multilingual NLP data sets. In *Findings of the Association for Computational Linguistics: NAACL 2024*, pages 3367–3382, Mexico City, Mexico. Association for Computational Linguistics.
- Farhan Samir and Miikka Silfverberg. 2023. Understanding compositional data augmentation in typologically diverse morphological inflection. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 277–291, Singapore. Association for Computational Linguistics.
- Gabriele Sarti, Arianna Bisazza, Ana Guerberof-Arenas, and Antonio Toral. 2022. DivEMT: Neural machine translation post-editing effort across typologically diverse languages. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 7795–7816, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Samuel M. Scheiner. 2012. A metric of biodiversity that integrates abundance, phylogeny, and function. *Oikos*, 121(8):1191–1202.
- Simeon Schüz, Ting Han, and Sina Zarrieß. 2021. Diversity as a by-product: Goal-oriented language generation leads to linguistic variation. In *Proceedings of the 22nd Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 411–422, Singapore and Online. Association for Computational Linguistics.

- Claude Elwood Shannon and Warren Weaver. 1949. A Mathematical Theory of Communication. University of Illinois Press, Urbana.
- Chenze Shao, Xuanfu Wu, and Yang Feng. 2022. One reference is not enough: Diverse distillation with reference selection for non-autoregressive translation. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3779–3791, Seattle, United States. Association for Computational Linguistics.
- Yibin Shen, Qianying Liu, Zhuoyuan Mao, Zhen Wan, Fei Cheng, and Sadao Kurohashi. 2022. Seeking diverse reasoning logic: Controlled equation expression generation for solving math word problems. In *Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 254–260, Online only. Association for Computational Linguistics.
- Benjamin Smith and J. Bastow Wilson. 1996. A Consumer's Guide to Evenness Indices. *Oikos*, 76(1):70–82. Number: 1 Publisher: [Nordic Society Oikos, Wiley].
- Bingyan Song, Chunguang Pan, Shengguang Wang, and Zhipeng Luo. 2021. DeepBlueAI at SemEval-2021 task 7: Detecting and rating humor and offense with stacking diverse language model-based methods. In *Proceedings of the 15th International Workshop on Semantic Evaluation (SemEval-2021)*, pages 1130–1134, Online. Association for Computational Linguistics.
- Feifan Song, Bowen Yu, Hao Lang, Haiyang Yu, Fei Huang, Houfeng Wang, and Yongbin Li. 2024. Scaling data diversity for fine-tuning language models in human alignment. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pages 14358–14369, Torino, Italia. ELRA and ICCL.
- Katherine Stasaski and Marti Hearst. 2022. Semantic diversity in dialogue with natural language

- inference. In Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 85–98, Seattle, United States. Association for Computational Linguistics.
- Andrew Stirling. 1994a. Diversity and ignorance in electricity supply investment. *Energy Policy*, 22(3):195–216.
- Andrew Stirling. 1994b. *Power technology choice:* putting the money where the mouth is? PhD, University of Sussex, Sussex.
- Andy Stirling. 2007. A general framework for analysing diversity in science, technology and society. *Journal of The Royal Society Interface*, 4(15):707–719. Number: 15 Publisher: Royal Society.
- Guy Tevet and Jonathan Berant. 2021. Evaluating the evaluation of diversity in natural language generation. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 326–346, Online. Association for Computational Linguistics.
- Brian Thompson and Matt Post. 2020. Paraphrase generation as zero-shot multilingual translation: Disentangling semantic similarity from lexical and syntactic diversity. In *Proceedings of the Fifth Conference on Machine Translation*, pages 561–570, Online. Association for Computational Linguistics.
- Rocco Tripodi, Simone Conia, and Roberto Navigli. 2021. UniteD-SRL: A unified dataset for spanand dependency-based multilingual and cross-lingual Semantic Role Labeling. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages 2293–2305, Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Ekaterina Vylomova, Jennifer White, Elizabeth Salesky, Sabrina J. Mielke, Shijie Wu, Edoardo Maria Ponti, Rowan Hall Maudslay, Ran Zmigrod, Josef Valvoda, Svetlana Toldova, Francis Tyers, Elena Klyachko, Ilya Yegorov, Natalia Krizhanovsky, Paula Czarnowska, Irene Nikkarinen, Andrew Krizhanovsky, Tiago Pimentel, Lucas Torroba Hennigen, Christo Kirov,

Garrett Nicolai, Adina Williams, Antonios Anastasopoulos, Hilaria Cruz, Eleanor Chodroff, Ryan Cotterell, Miikka Silfverberg, and Mans Hulden. 2020. SIGMORPHON 2020 shared task 0: Typologically diverse morphological inflection. In *Proceedings of the 17th SIGMORPHON Workshop on Computational Research in Phonetics, Phonology, and Morphology*, pages 1–39, Online. Association for Computational Linguistics.

Tharindu Cyril Weerasooriya, Alexander Ororbia, Raj Bhensadadia, Ashiqur KhudaBukhsh, and Christopher Homan. 2023. Disagreement matters: Preserving label diversity by jointly modeling item and annotator label distributions with DisCo. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 4679–4695, Toronto, Canada. Association for Computational Linguistics.

Xuanfu Wu, Yang Feng, and Chenze Shao. 2020. Generating diverse translation from model distribution with dropout. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1088–1097, Online. Association for Computational Linguistics.

Yu Xia, Xu Liu, Tong Yu, Sungchul Kim, Ryan Rossi, Anup Rao, Tung Mai, and Shuai Li. 2024. Hallucination diversity-aware active learning for text summarization. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 8665–8677, Mexico City, Mexico. Association for Computational Linguistics.

Jingjing Xu, Xuancheng Ren, Junyang Lin, and Xu Sun. 2018. Diversity-promoting GAN: A cross-entropy based generative adversarial network for diversified text generation. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3940–3949, Brussels, Belgium. Association for Computational Linguistics.

Vikas Yadav, Hyuk joon Kwon, Vijay Srinivasan, and Hongxia Jin. 2024. Explicit over implict: Explicit diversity conditions for effective question answer generation. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and*

Evaluation (LREC-COLING 2024), pages 6876–6882, Torino, Italia. ELRA and ICCL.

Cai Yang and Stephen Wan. 2022. Investigating metric diversity for evaluating long document summarisation. In *Proceedings of the Third Workshop on Scholarly Document Processing*, pages 115–125, Gyeongju, Republic of Korea. Association for Computational Linguistics.

Jingfeng Yang, Diyi Yang, and Zhaoran Ma. 2020. Planning and generating natural and diverse disfluent texts as augmentation for disfluency detection. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1450–1460, Online. Association for Computational Linguistics.

Yuting Yang, Pei Huang, Feifei Ma, Juan Cao, and Jintao Li. 2024. PAD: A robustness enhancement ensemble method via promoting attention diversity. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pages 12574–12584, Torino, Italia. ELRA and ICCL.

Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William Cohen, Ruslan Salakhutdinov, and Christopher D. Manning. 2018. HotpotQA: A dataset for diverse, explainable multi-hop question answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2369–2380, Brussels, Belgium. Association for Computational Linguistics.

Taro Yano, Kunihiro Takeoka, and Masafumi Oyamada. 2024. Relevance, diversity, and exclusivity: Designing keyword-augmentation strategy for zero-shot classifiers. In *Proceedings of the 13th Joint Conference on Lexical and Computational Semantics (*SEM 2024)*, pages 106–119, Mexico City, Mexico. Association for Computational Linguistics.

Da Yin, Liunian Harold Li, Ziniu Hu, Nanyun Peng, and Kai-Wei Chang. 2021. Broaden the vision: Geo-diverse visual commonsense reasoning. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 2115–2129, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Yu Yu, Shahram Khadivi, and Jia Xu. 2022. Can data diversity enhance learning generalization? In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 4933–4945, Gyeongju, Republic of Korea. International Committee on Computational Linguistics.

Huajian Zhang, Yumo Xu, and Laura Perez-Beltrachini. 2024a. Fine-grained natural language inference based faithfulness evaluation for diverse summarisation tasks. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1701–1722, St. Julian's, Malta. Association for Computational Linguistics.

Hugh Zhang, Daniel Duckworth, Daphne Ippolito, and Arvind Neelakantan. 2021. Trading off diversity and quality in natural language generation. In *Proceedings of the Workshop on Human Evaluation of NLP Systems (HumEval)*, pages 25–33, Online. Association for Computational Linguistics.

Tianyi Zhang*, Varsha Kishore*, Felix Wu*, Kilian Q. Weinberger, and Yoav Artzi. 2020. Bertscore: Evaluating text generation with bert. In *International Conference on Learning Representations*.

Xinran Zhang, Maosong Sun, Jiafeng Liu, and Xiaobing Li. 2023. Lingxi: A diversity-aware Chinese modern poetry generation system. In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 3: System Demonstrations), pages 63–75, Toronto, Canada. Association for Computational Linguistics.

Yusen Zhang, Nan Zhang, Yixin Liu, Alexander Fabbri, Junru Liu, Ryo Kamoi, Xiaoxin Lu, Caiming Xiong, Jieyu Zhao, Dragomir Radev, Kathleen McKeown, and Rui Zhang. 2024b. Fair abstractive summarization of diverse perspectives. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 3404–3426, Mexico City, Mexico. Association for Computational Linguistics.

Yaoming Zhu, Sidi Lu, Lei Zheng, Jiaxian Guo, Weinan Zhang, Jun Wang, and Yong Yu. 2018.

Texygen: A benchmarking platform for text generation models. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, SIGIR 2018, Ann Arbor, MI, USA, July 08-12, 2018*, pages 1097–1100. ACM.