A Survey on Representing Linguistic Style: Challenges and Opportunities

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Abstract

Although representation learning has transformed semantic modeling in NLP, representations of linguistic style remain underexplored—partly due to conflicting definitions of style within and beyond NLP or unclear immediate advantages of separate style representations. In this survey, we provide an overview of style conceptualizations across different research fields with a focus on NLP and (socio-)linguistics and suggest a working definition of style for practitioners. Then, we review methods for creating and evaluating style representations. We conclude by discussing how style representations can make crucial contributions to the modern NLP pipeline (e.g., in dataset curation or evaluation) and to the application of NLP methods in other fields. Throughout our survey, we sketch pressing open research questions in the landscape of style representations, emphasizing the need for better evaluation approaches and more comprehensive style representations.

1 Introduction

The Lego Grad Student[1] posted in July 2020,

> *Videoconferencing from his apartment with his advisor, the grad student feels like the victim of a home invasion.*

Now consider a rephrasing by GPT-5.2 using the Wikipedia-style prompt from Maini et al. (2024):

> *While conducting a videoconference with his academic advisor from his apartment, the graduate student experiences the interaction as an intrusion into his private living space.*

The linguistic style of the original post (e.g., more informal, compact) likely contributed to the 3k likes it received. Style can affect a reader's perception as it can, for example, influence engagement (Munaro et al., 2024; Banerjee and Urminsky, 2025) and change the persuasiveness of arguments (El Baff et al., 2020; Parhankangas and Renko, 2017). Moreover, style also influences human quality ratings of generated content[2] (Cai et al., 2024; Wu and Aji, 2025) leading to one of our main takeaways: *If you care about LLMs, then style matters.*

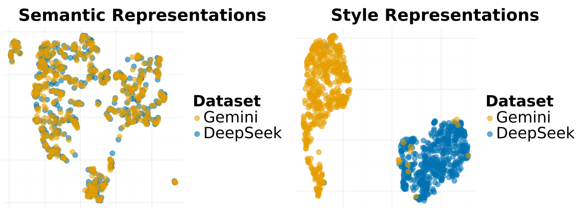

Figure 1: **Semantic representations differ from style representations** We compare reasoning traces from Muennighoff et al. (2025), generated with Gemini and DeepSeek for the same reasoning problems. Style representations can distinguish between the two models—confirming results in Rivera Soto et al. (2023)—while semantic representations overlap. See §B.1 for details.

However, style is often disregarded in NLP. As a result, language models can be brittle across (or not *robust* to) style-like features: rephrasing prompts in different styles leads to different performances (Mizrahi et al., 2024; Wahle et al., 2024); LLM judges can prefer long, formal, or synthetic texts over relevance (Cao, 2025; Feuer et al., 2025; Wu and Aji, 2025); machine translations sound older and more male than the original (Hovy et al., 2020); models are biased against non-majority varieties (Fleisig et al., 2024; Hofmann et al., 2024; Liang et al., 2023) and perform worse on non-standard spellings (Ebrahimi et al., 2018; Li et al., 2019), simple and informal styles, and genres like poetry (Anschütz et al., 2025; Cao, 2025; Qi et al., 2021; Zhao et al., 2025). This brittleness might increase as we train on more synthetic data (Guo et al., 2024).

[1] The "Lego Grad Student" is an online creator that received engagement on Twitter and Instagram with photos of LEGO figures playing out scenes in a grad student's life. This message was posted during the COVID-19 pandemic.

[2] People might prefer the style of certain LLMs over others, e.g., Claude's style over ChatGPT's, or want to customize an LLM's style (OpenAI, 2025); see Personalization in §5.2.

Style representations (i.e., vectors with entries that are optimized for style information) can help: They can improve model robustness by supporting the curation of stylistically diverse (post-)training datasets, support text generation in and evaluate adherence to a target style, help machine text detection, and enable new tasks (e.g., retrieval of documents in a target style). In the social sciences and humanities, they can support the analysis of literary texts and style dynamics in dialogue. A detailed discussion of these possibilities follows in § 5.

Semantic representations are often also sensitive to style information as word prediction tasks also need style information (Nguyen and Grieve, 2020; Goldberg, 2019; Tenney et al., 2018; Miaschi et al., 2020; Wegmann and Nguyen, 2021). However, we believe that semantic representations alone are insufficient for modeling style: They are usually not evaluated on style-related tasks (Enevoldsen et al., 2025; Muennighoff et al., 2023) and have limited sensitivity to style (e.g., Mickus and Copot, 2024; Zhang et al., 2023b). Most importantly, they are trained to focus primarily on semantic information, making it difficult to investigate the style of texts separately from content (cf. Fig. 1).

In contrast to semantic representations, only a few community-vetted and broadly tested methods exist for representing the style of texts. **The main goals of this paper are** to promote the wider adoption of linguistic style representations within and beyond NLP, guide practitioners towards key resources, and highlight key challenges and research directions in the study of style representations.

With this paper, we contribute:

- an overview of style definitions in linguistics and NLP, including our own definition (§ 2)
- an overview of methods for representing (§ 3) and evaluating (§ 4) style representations
- a discussion of why style representations are useful for modern NLP and other fields (§ 5)
- 🔧 practical resources, ❓ open research questions, and 📣 calls to action (several sections)
- 🔧 an expanding GitHub repository[3] collecting datasets, tools, and other resources

Despite the significant attention given to style in other modalities (e.g., speech), text-based NLP has lagged behind, highlighting the need for this survey. In line with this limited coverage, most of the work we discuss focuses on English texts, but we urge the NLP community to consider more languages and modalities in the future.

[3] `https://github.com/AnnaWegmann/StyleSurvey/` and `https://annawegmann.github.io/StyleSurvey/`

2 Style conceptualizations

> Linguists often define style as a distinctive pattern in language for some object of study (e.g., for an author or group), while NLP researchers often use "style" more loosely.

2.1 Style in linguistics

Researchers working with style often aim to describe a text's structural linguistic features (i.e., how something is said) more so than its semantic meaning[4] (i.e., what is said). However, some linguistics researchers might disagree with such a separation (see § C), finding that style and content are intertwined, at least to some extent (cf. § 2.3). Studying style might then be understood as studying what makes a phrasing distinctive within a set of possibilities (Irvine, 2001), for instance, how speakers use linguistic choices related to external factors like social background, identity, or register. Overall, we emphasize that *style is an elusive term that has been defined in many different, sometimes inconsistent, ways in linguistics and other fields*.[5]

What are the objects of study? Style is usually studied in a relative sense, as a distinctive difference between objects of study (Irvine, 2001); however, these objects vary. In (socio-)linguistics, style has often been discussed as inter-individual variation—the idiosyncratic choices that potentially distinguish individuals from each other, often referred to as their *idiolect* (Coulthard, 2004)—and intra-individual variation (Bell, 1984; Irvine, 2001; Labov, 2006; Meyerhoff, 2006; Wagner, 2025)—the change in the same speaker's language across situations. Famously, Labov (1972) discovered that individuals' speaking style becomes more formal as they pay more attention to their speech and more casual as they pay less attention. Sociolinguists have additionally studied style as inter-group variation—differences in the language of people identifying with different social groups (Bell, 1984; Eckert, 2008; Irvine, 2001; Kristiansen, 2024). For example, *g*-dropping (*going* vs. *goin'*)

[4] Or: referential meaning (Campbell-Kibler, 2011; Labov, 1972; Lavandera, 1978; Nguyen et al., 2016, 2021). Two variants have the same referential meaning if they are the same in a truth-conditional sense (i.e., true in exactly the same situations), while the "social" or "stylistic significance" might differ considerably (Labov, 1972; Weiner and Labov, 1983).

[5] See § C for an overview of other areas interested in style.

may indicate a person's association with a southern U.S. region (Campbell-Kibler, 2007).

Genres and registers (or domains) have also been objects of style research (Biber and Conrad, 2019; Grieve, 2023). Literature from a historical period, novels by a specific author, news reports, and blogs can display very different linguistic patterns, which might be called the style of that historical period, literary author, news report, or blog (Biber and Conrad, 2019; Grieve et al., 2011; Hicke and Mimno, 2025; Irvine, 2001).

Researchers have considered more objects of study than we discuss, like the communication environment (e.g., speech before a crowd or a courtroom in Ervin-Tripp, 2001) or the communicative manner (spontaneous vs. read speech in Williams and King, 2019). Researchers can also study combinations of these objects (e.g., courtroom speeches by one individual) or an object only in certain contexts (e.g., a social group discussing a certain topic). For example, Holliday (2021) finds that biracial Black men displayed fewer African American[6] intonational features when discussing police narratives.

What is the function of style? Style might also be defined as patterns in language tied to a specific function. Some scholars argue that style is fundamentally embedded in social meaning, indexing social background and shaping social identity (Campbell-Kibler et al., 2006; Coupland, 2007; Eckert, 2008, 2012). For example, Labov (1972) found that differences in the pronunciation of /r/ correlated with social class, and Eckert (1989) found that self-identified "burnouts" at a Detroit school used more non-standard linguistic features (e.g., *gonna*) than college-bound "jocks" (e.g., *going to*).

Labov originally viewed a speaker's vernacular as a reflection of their social identity, not an active choice (Labov, 1972). More recent sociolinguistic approaches see style as more agentive—not only reflecting identity but also performing and constructing it (Eckert, 2012). For example, the development of linguistic practices of trans activists can be tied to their agency in creating identity (Zimman, 2019), and speakers may choose styles for performative functions like getting attention (Ervin-Tripp, 2001).

[6]While several linguistic features can describe both styles and dialects, dialects are typically not called styles but distinct types of language variation more clearly tied to speakers' social backgrounds and geographic regions (Biber and Conrad, 2019; Grieve et al., 2025). Nonetheless, some researchers also consider dialects as a kind of social style (Coupland, 2007). We do not specifically exclude dialects in our definition (§2.3), but our focus remains on non-dialectal stylistic variation.

Style can serve communicative functions in an interaction (Coupland, 2007): Speakers may align with (accommodate) or distance themselves from the style of interlocutors or audiences (Bell, 1984; Giles and Powesland, 1975; Giles et al., 1991; Khaleghzadegan et al., 2024), thereby shaping social relationships and interactions (Coupland, 2007). For example, Bell (2014) found that New Zealand newscasters shifted their pronunciation when talking to audiences of higher or lower status.

Finally, some consider style to be aesthetic, with no or limited function, and instead prefer the term *register* for varieties of language associated with a particular situational context (Biber and Conrad, 2019). When considering register as style, style might serve further functions like structuring discourse and fulfilling communicative purposes.

2.2 Style in NLP

Some work in NLP uses the term style in ways broadly consistent with linguistics, aiming to study formal/informal styles and literary authorial styles (e.g., Jhamtani et al., 2017; Rao and Tetreault, 2018; Wegmann and Nguyen, 2021); however, others increasingly use style as an umbrella term for general attributes of texts that vary across datasets (Jin et al., 2022) such as the sentiment of a text (Reif et al., 2022; Shen et al., 2017), but do not necessarily align with a typical linguistic definition of style.

Separating content and style As in linguistics (§ 2.1), work in NLP finds that content and style are often correlated (Jafaritazehjani et al., 2020; Mikros and Argiri, 2007). Still, separating style and content tends to be a natural distinction for many NLP applications. Specifically, NLG systems have to fundamentally determine what information to generate—the knowledge, or message—and what style to generate it in (Gatt and Krahmer, 2018). While neural NLG systems often handle content and style implicitly, generating texts end-to-end without explicit planning stages, the distinction between style and content remains useful in practice, for example, when curating datasets, rephrasing and adapting texts, or evaluating the factual correctness of model outputs (§ 5).

2.3 A working definition for style in NLP

We propose a working definition of style for NLP practitioners.[7] Throughout the paper, we consis-

[7]Our definition does not specifically exclude concepts like dialects, registers, or varieties for practical reasons: (i) the

tently use the same colors for the same concepts.

Definition A linguistic style consists of ***distinctive patterns in language use*** for an object of study (e.g., individuals, a group of authors in a given register) in its lexical, syntactic, morphological, orthographic, discourse, phonetic, etc. composition. These patterns should not chiefly measure, but can correlate with, semantic meaning.

For example, a person discussing American football might talk more casually than when discussing ballroom dance, yet some underlying linguistic features may remain consistent in both situations and carry social meaning (§2), e.g., about the speaker's upbringing. When studying style, we might study the differences or commonalities between discussing American football and ballroom dance, depending on the object of study, i.e., whether we are currently interested in a specific individual, demographic, situation, etc.

3 Representing style

Linguistic style is usually operationalized with patterns in linguistic features like function words or automatically-learned representations like neural text representations.

3.1 Predefined features

Style is often operationalized as the systematic variation of linguistic features, which can span various linguistic levels including morphology, orthography, syntax, and discourse (Biber and Conrad, 2019; Crystal and Davy, 1969; Grieve, 2007; Kniffka, 2007; Labov, 1972; Neal et al., 2017; Stamatatos, 2009). 🔧 App. Tab. 1 gives example features (e.g., *g*-dropping) at each level; 🔧 §D lists tools for extracting predefined features. The primary appeal of predefined features is that they are supported by linguistic theory, have been tested extensively, and are generally interpretable (i.e., have a meaning understandable to humans). The features can be used with statistical approaches like logistic regression or dimensionality reduction with factor analysis to determine how important each feature is. This transparency is especially important in high-stakes settings, such as forensic linguistics, where it is crucial to explain a model's decision-making process (Argamon, 2018; Grant, 2022).

One such feature-based style operationalization is stylometry, which measures the frequencies of linguistic features that help discriminate between author styles. There is no fixed set of features that work for every individual, despite much work attempting to find one (Juola, 2006; Nini, 2023); instead, the features often depend on the nature of the data (e.g., genre, register, amount of data, language) (Argamon, 2018). Nonetheless, function words (i.e., words like prepositions and conjunctions that primarily serve a grammatical role) and character n-grams (i.e., n successive characters), in particular, have proven quite effective at discriminating authors (Grieve, 2007; Houvardas and Stamatatos, 2006; Peng et al., 2003; Kestemont, 2014; Mosteller and Wallace, 1963) and speakers (Aggazzotti and Smith, 2025; Aggazzotti et al., 2024; Doddington, 2001; Sergidou et al., 2023; Tripto et al., 2023). N-grams, whether character, token/word, or part-of-speech tag n-grams, are also beneficial because they work across many languages.

Other feature operationalizations serve different purposes related to style. For example, Multidimensional Analysis (MDA) (Biber, 1988) is used to determine how texts differ in their communicative function and originally relied on mostly grammatical category-related features (e.g. nouns, verbs); however, modern extensions (e.g., Clarke and Grieve, 2017; Grieve et al., 2011) additionally include more complex features, such as syntactic constructions and semantic classes.

3.2 Automatically-learned features

By automatically-learned features or embeddings, we mean vector representations of text produced by (usually neural) models. In contrast to predefined features, automatically-learned features do not rely on specific, established features but can automatically discover style patterns. Further, they often perform better than predefined features on downstream tasks, but are usually less interpretable. Because it is difficult to operationalize definitions of style, models are usually optimized in proxy downstream tasks, such as authorship verification or style transfer. 🔧 See §D for links to models.

Authorship verification The most popular approach to date trains models with a contrastive objective (Dong and Shen, 2018; Khosla et al., 2020) to learn representations where two text samples are

separation between such terms is not consistent in linguistics, and (ii) computational style representations are commonly expected to be sensitive to dialect, register, and variety information (§4). We leave further practical disentanglement between style and other terms for future work.

close together in vector space if they are written by the same author and far apart otherwise (Andrews and Bishop, 2019; Khan et al., 2021; Kim et al., 2025; Man and Huu Nguyen, 2024; Rivera Soto et al., 2021; Sawatphol et al., 2022; Thakrar et al., 2025; Wang et al., 2023; Wegmann et al., 2022). Representations trained on this task have been shown to capture stylistic information (Wang et al., 2023; Wegmann and Nguyen, 2021).

Since training datasets may contain undesired correlations—for example between style and content when an author only writes about one topic—some work creates harder positive (i.e., same author) and negative (i.e., different author) pairs to improve disentanglement (Man and Huu Nguyen, 2024; Patel et al., 2025). For example, Wegmann et al. (2022) use negative pairs that are approximately about the same topic, and Patel et al. (2025) leverage LLMs to create a synthetic dataset of near-exact paraphrases by varying predefined features. Building on such disentanglement strategies, recent work generalizes style representations to multilingual settings (Kim et al., 2025; Qiu et al., 2025), where negative pairs must be carefully constructed to avoid trivial cross-lingual differences.

Style transfer Another line of work learns representations via style-transfer, aiming to rewrite text for a stylistic attribute without altering its semantic meaning (Cheng et al., 2020b; John et al., 2019; Shen et al., 2017; Zhu et al., 2024). For instance, a model may be trained to convert formal text into informal text, conditioned on both the input and an embedding of the target style. Under this objective, embeddings learn features indicative of informality.

These methods usually rely on explicit style-content disentanglement and tend to learn representations that are more narrow in scope, often tied to single attributes (e.g., politeness) or differences between two corpora (Shen et al., 2017). John et al. (2019) train an auto-encoder to produce a style and a content vector, imposing a style classification loss on the style representation and an adversarial style classification loss on the content vector. Cheng et al. (2020b) minimizes the estimated mutual information between the style and content representations.

Interpretable LLM-guided stylometry A distinctive method is LISA (Patel et al., 2023), which learns embeddings where each dimension is an *interpretable* feature (e.g., use of an elongated word). The authors create a synthetic dataset by prompting GPT-3 for stylometric features, then train an

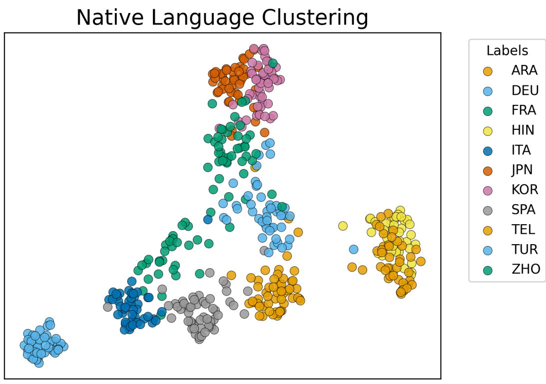

Figure 2: **By-product of authorship verification training** Stylistic representations, though trained on the "idiolectal" authorship verification task, cluster TOEFL (Test of English as a Foreign Language) essays by the native language of the writer. See §B.3 for more details.

EncT5 (Liu et al., 2022) model to predict the presence of each feature in a text sample. Because distances in this space are not well-defined, they fit a linear transformation on the authorship verification task. LISA is the first method to use LLM-based automatic labeling for style representations, offering a middle ground between hand-crafted features derived by human experts and automatically-learned representations. However, limitations of LLMs might need to be considered (§1, §5.1).

3.3 The future of style representations

📣 Define what we want to represent

Training representations on the authorship verification task implicitly defines style as the idiosyncrasies exhibited by authors in certain corpora (Zhu and Jurgens, 2021). However, because the contrastive dataset might never pair authors from the same social group as negatives, a representation may inadvertently primarily encode group-level features. Indeed, we find that various "idiolectal" style representations encode features discriminative of writers' native language in Fig. 2. We call on the community to explicitly define their object of study (e.g., idiolect, cf. §2.3), use learning approaches like hard negatives to control for other concepts (e.g., variation within the same social group), and evaluate whether representations primarily capture variations for the defined object of study.

❓ Build general-purpose style embeddings

It remains an open challenge to learn general-purpose style embeddings that cover as many objects of study as possible and are, for example, sensitive to individual, group, register, and time period variation at the same time. For this, new training objectives could explicitly target different objects of study. Using multiple objectives might require stronger disentanglement objectives, for example, based on minimizing mutual information of two representations (Cheng et al., 2020a), adversarial objectives (John et al., 2019), or by employing VAEs to explicitly disentangle between syntax and semantics (Chen et al., 2019; Bao et al., 2019).

❓ Improve training

There are several other areas in training that remain underexplored. For example, fine-tuning newer encoder models like ModernBERT (Alshomary et al., 2025b), designing tokenizers specifically for style representations (Wegmann et al., 2025), and pooling not only the last, but several or all, encoder layers might improve performance (Alshomary et al., 2025b).

❓ Construct interpretable embeddings

An open question is how to learn representations with interpretable dimensions that are still as performant as their uninterpretable counterparts. Such work may benefit from sparse autoencoders—which have recently been shown to automatically learn interpretable features (Huben et al., 2024)—or from combining predefined features with neural training—for example, by training models to classify predefined features (cf. Alkiek et al., 2025).

4 Evaluating style representations

> To develop better style representations, we must be able to compare and evaluate them, but no standard currently exists.

4.1 Previous approaches

We divide evaluation approaches according to our definition of style (§ 2.3), grouping them into predefined features, objects of study—including authorship verification—and content-independence.

On predefined features Learned representations (§ 3.2) can be evaluated on their sensitivity to predefined features (§ 3.1). Various studies use probing classifiers (Adi et al., 2017; Köhn, 2015) as well as recurrent/recursive neural networks (Belinkov et al., 2017; Shi et al., 2016) to assess which linguistic features are captured by representations. For example, Alshomary et al., 2025b probe style representations on morphology and syntax. However, probing has limitations, such as uncertainty over how to interpret classifier performance (Belinkov, 2022). Other approaches are sparse, but include studying performance loss on style tasks when removing syntactic and discourse information from texts via shuffling (Zhu and Jurgens, 2021) and evaluating the cosine similarity between texts that include the same predefined features like contraction usage or use of passive voice (Patel et al., 2025; Wegmann and Nguyen, 2021).

On objects of study Representations have also been evaluated for their ability to classify common objects of study (§ 2), including probing and classifying (i) literary authors (Wang et al., 2023), (ii) book genres (Maharjan et al., 2019), (iii) registers (Alkiek et al., 2025), and (iv) demographic information of authors like gender or age (Ding et al., 2019; Kang et al., 2019; Kang and Hovy, 2021). Other work examines whether representations of formal/-complex texts are similar to other formal/complex texts (Wegmann and Nguyen, 2021). Further, Terreau et al. (2021) use representations to predict an author's distribution on predefined features.

Authorship attribution Many works evaluate style representations according to their usefulness for authorship attribution or verification tasks (Alkiek et al., 2025; Ding et al., 2019; Maharjan et al., 2019; Patel et al., 2025), including testing whether a representation clusters documents by the same author together (Hay et al., 2020). Datasets and domains like e-mails, blogs, Reddit, Amazon Reviews, Yelp reviews, fanfiction, or shared PAN tasks[8] from the years 2011–2025 (Argamon and Juola, 2011; Bevendorff et al., 2025a) are commonly used. 🔧 See Huang et al. (2025) and our GitHub page for a collection of typical datasets. Recently, transcribed spoken domains, such as telephone conversations, interviews, speeches, and podcasts, have also been used (Aggazzotti et al., 2024, 2025b; Tripto et al., 2023). However, without careful preparation, datasets might contain named entities, leakage between train and test sets (Brad et al., 2022; Sawatphol et al., 2024), or spurious correlations with topic (Wegmann et al., 2022), making performance less interpretable. There are promising contributions tackling such issues, like Israeli et al. (2025) and Khan et al. (2021), who provide large sets of authors across different topics on Wikipedia and Reddit, Tripto et al. (2023), who provide speech transcripts across various reg-

[8] 🔧 `https://pan.webis.de/shared-tasks`

isters and topics, and Tyo et al. (2022) who design a benchmark across domains for authorship attribution and verification. However, researchers typically use a differing selection of tasks, data, domain combinations, or splits, making performance scores incomparable across different studies.

Content-independence Even though it is debatable whether linguistic style generally excludes content information (§2), style representations are commonly tested on "content-independence". This has been evaluated by studying the loss of performance on style-related NLP tasks (like authorship verification or attribution) when masking out less frequent words or "content words" (Stamatatos, 2017; Wang et al., 2023; Zhu and Jurgens, 2021) or when changing the style of a text with an automatic paraphraser (Wang et al., 2023). Other approaches test whether style representations are more sensitive to style changes than to content changes (Wegmann and Nguyen, 2021; Wegmann et al., 2022), whether they can distinguish speakers discussing the same conversational topic (Aggazzotti et al., 2024, 2025b), and whether they perform poorly on semantic tasks like topic classification (Wang et al., 2023). Generally, few style representations reach high scores on content-independence (🔧 App. Tab. 3) and might benefit from more exhaustive content disentanglement.

4.2 The future of style evaluation

📣 Increase interpret- and explainability

The evaluation of learned style representations on predefined features is not yet systematic, but is promising to pursue, as it can build on rich literature in linguistics and stylometry (§ 2.1, § 3.1) and can help make learned representations more interpretable. Further, there is only limited work on explaining learned style spaces. Alshomary et al., 2025a pioneer this direction by generating explanations on why embeddings cluster certain authors.

❓ Leverage measurement theory

In the social sciences, measures are commonly assessed for *reliability* (do measures return the same result with repeated measurement?) and *validity* (do measures capture the concept of interest?). Measurement theory could provide the evaluation of style embeddings and the construction of style benchmarks with a theoretical framework, highlight gaps, and provide inspiration for future methods. 🔧 See Trochim et al. (2015) for more on measurement theory. See Fang et al. (2022) for examples of how to apply measurement theory to embeddings and Bean et al. (2025) for recommendations on how to construct valid benchmarks. We give examples of how measurement theory might be applied for style embeddings and benchmarks in App. § E.

📣 Develop standard benchmarks

Only a few contributions aim to systematically evaluate representations on linguistic style, leaving this area of research behind semantic embeddings and approaches like MTEB (Enevoldsen et al., 2025; Muennighoff et al., 2023). We discuss some notable pioneers: Kang and Hovy (2021) collected the largest dataset to date for style classification; however, several of their classes (e.g., sentiment) would not be considered style in linguistics. Further, STEL (Wegmann and Nguyen, 2021) is a theory-driven benchmark on single linguistic properties and broader style categories that evaluates representations with cosine similarities—thus not needing training. Neither approach covers a wide range of styles or domains or clearly defines an object of study (cf. §2.3). Providing an open, easily accessible, high quality, and diverse style benchmark spanning multiple objects of study like registers and authors would be a significant contribution.

5 What style representations enable

> Style representations can make crucial contributions to the modern NLP pipeline and to applications of NLP methods.

We provide a selection of examples of what style representations can enable. We list a few more in § F, including authorship attribution, bias reduction, reducing spurious correlations in annotations, and improving generalization across styles.

5.1 An improved NLP pipeline

📣 Curate multi-stage training datasets

LLMs are often not robust to stylistic variation (§ 1). Manipulating and diversifying the style of texts in in-context learning (ICL) examples as well as pre- and post-training datasets—for example, by stratified curation or rephrasing in different styles—has helped output diversity and performance across stylistic variation (Chen et al., 2024b; Lambert et al., 2025; Levy et al., 2023; Maini et al., 2024). Curriculum learning or multi-stage training found increased success recently (OLMo et al., 2025; Ettinger et al., 2025; Allal et al., 2025). We believe that style representations can be a crucial tool to monitor the overall stylistic diversity of a dataset (cf. Nguyen and Ploeger, 2025) and can help select data points for training that increase or decrease stylistic diversity according to a curriculum. Further, they can help rephrase texts in other styles (cf. Maini et al., 2024) using style transfer methods (§5.1) and select datapoints that align with a target style in ICL and (post-)training datasets.

📣 **Diversify style in evaluation datasets**

Both style and content influence human preference judgments (Cai et al., 2024; Chen et al., 2024a; Singhal et al., 2024; Tianle Li, 2024). However, state-of-the-art performance is often established only on content tasks (mostly NLU and reasoning) using texts with limited stylistic variation (Guo et al., 2025; Truong et al., 2025). This might obfuscate a model's ability to generalize to other domains or understand and generate diverse or preferred styles.[9] Instead, benchmarks could be composed not only based on what they test, but also based on whether their datasets or tasks cover different or expected regions of the style embedding space.

5.2 Various other applications

Generating in specific styles Representations of style can help generate text in a specific style, or adapt to different domains (Horvitz et al., 2024a,b; Liu et al., 2023; Zhang et al., 2023a). Such style steering approaches can enable accessibility in language generation (Anschütz et al., 2025; Cao et al., 2020; Surya et al., 2019)—for example, by simplifying a text for a child or summarizing a text for a non-expert. The style of generated texts is often evaluated by comparing their style representations to those of a target style (Chim et al., 2025; Horvitz et al., 2024a; Jangra et al., 2025; Liu et al., 2023).

Personalization Interest in personalized model responses has grown recently (Zhang et al., 2025b; Liu et al., 2025). Style plays a crucial role in personalization (Zhang et al., 2025b; Liu et al., 2025), and style representations could be used to recognize the style of humans, infer their preferences, and adapt generated responses to them (Zhang et al., 2025a).

Machine text detection There is a growing concern about the misuse of LLMs, including disinformation, spam, and plagiarism. Recent work (Bevendorff et al., 2025b; Elkhatat et al., 2023; Gehrmann et al., 2019; Kumarage et al., 2023; Sun et al., 2025; Uchendu et al., 2020) shows that LLMs exhibit idiosyncrasies that distinguish their writing from human writing. Detectors that use style embeddings have been effective in in-domain and cross-domain settings (Kim et al., 2025; Rivera Soto et al., 2023).

Privacy On the flip side of attribution and detection is the task of obfuscating someone's identity.[10] Style representations can help determine if text that has been anonymized, such as via paraphrasing, sufficiently removes someone's style and protects their privacy (Aggazzotti et al., 2025a; Alperin et al., 2025; Bao and Carpuat, 2024; Shokri et al., 2025).

📣 **Push style representations as a foundational method for NLP and other fields**

Just as semantic embeddings have become foundational, style representations could also be foundational across fields. Next to the mentioned uses, they could help retrieve documents with a (dis-)similar style to a search query (Cao, 2025), track style shift in dialogue in sociolinguistics (Nguyen, 2025), or analyze literary text in the digital humanities (Hicke and Mimno, 2025), with current embeddings already seeing significant adoption.[11]

6 Conclusion

With this paper, we hope to have demonstrated the potential of style representations for the NLP community. We call on researchers to use clearer definitions of style, to more explicitly disentangle evaluation and training approaches, and to develop evaluation methods into a standard. We end by noting that style has unique properties that may require unique considerations and methodologies. Among these, the style of a text is inherently relative. For example, it might be clearer and more relevant to judge if a text (e.g., *How are you?*) is more formal than another (e.g., *What's up?*) rather than if it is formal in isolation; consider also App. Fig. 3 and Irvine (2001). This relativity may require new solutions in training and evaluating representations—for example, curating training data with hard positives and negatives positioned in relation to each other, or testing whether representations correctly rank sentences along a stylistic dimension.

[9]For example, textbooks might not be all you need (cf. Li et al., 2023) for perplexity across registers (Maini, 2023).

[10]For example, see the PAN Author Masking series at https://pan.webis.de/shared-tasks.html#author-masking.

[11]https://huggingface.co/AnnaWegmann/Style-Embedding reached 200k downloads in October 2025.

Limitations

📣 Consider style in modalities other than text.

Many of the examples and citations throughout this paper refer to text-based style since the limited style research in NLP has focused on written language, but linguistic style also manifests, and is perhaps better studied, in other modalities like speech (e.g., tone of voice), gestures, and vision (e.g., image generation). We leave considerations for representing style in other modalities for future work.

📣 Give more attention to style in languages other than English.

The bulk of the work we discuss considers style in English. For example, we mainly discuss definitions of style considered by American scholars (cf. § 2.1), and we discuss predefined features mainly for English (cf. § 3.1)—for instance, "*g*-dropping" is an English-specific marker. Different scripts and languages will usually need different predefined features and have a different history regarding style definitions and sociolinguistic research (see also Ball et al., 2023). However, our discussed approaches to automatically learn and evaluate representations should largely transcend languages and scripts as long as architectural components (e.g., tokenizers), evaluation datasets, and predefined features are adapted for optimal performance. We believe that developing style representations for languages other than English is a crucial future step and call on the community to continue pioneering work like Kim et al. (2025) and Qiu et al. (2025).

Why not use a different term instead of style?

> *...the extremely broad and ambiguous reference of the term [style] in everyday use has not made its status as a technical linguistic term very appealing.*
>
> — David Crystal

Scholars, such as Crystal (2011), have argued against using the term style at all due to its increasingly vague and colloquial use. Instead, researchers have opted to describe the specific phenomenon they are interested in (e.g., syntactic variation) and use less over-defined terms (e.g., language variation). While that can be helpful in some cases, we argue that using the term style is still worthwhile because (i) the term is used regularly in NLP (with 200 publications in the ACL Anthology mentioning "style" in the title or abstract in 2024) highlighting the interest in the term; (ii) style seems to provide a more concise and intuitive label than alternatives like "distinctive patterns in the used language varieties" or "systematic variation in textual features"; and (iii) the term style can draw from decades of theoretical foundation in stylometry and sociolinguistics.

Style is a concept used in many fields. Why focus on the ones discussed in the paper? Next to NLP, we focus on definitions and concepts of style used in sociolinguistics, linguistics, stylometry, forensic linguistics, and corpus linguistics (§ 2, see an overview of the fields in § C). To the best of our knowledge, these are the most active areas already using, or intuitive areas that could profit from using, computational methods for analyzing style. Further, we believe that sociolinguistics is particularly relevant to consider, as its study of the interaction between language and society has unique potential to inform NLP methods (Nguyen, 2025), especially as NLP models are increasingly used within, and have growing impact on, society.

Ethical considerations

Style modeling is closely related to *author profiling* (cf. § 4)—the task of recovering author characteristics based on the text they wrote (Nguyen et al., 2013; Rangel et al., 2013). Note that author profiling can be useful for improving performance on some NLP tasks (Hovy, 2015); however, identifying an author's gender, age, personality type, etc. has increasingly been criticized for bias and privacy concerns (Brennan et al., 2012; Elazar and Goldberg, 2018; Li et al., 2018; Lison et al., 2021).

Integrating more language diversity, and with it social factors, into NLP is a double-edged sword: There are clear advantages to integrating more diversity into NLP models and, specifically, representing minorities to increase the fairness and representativeness of NLP models (Bird and Yibarbuk, 2024; Grieve et al., 2025; Hovy and Yang, 2021; Markl et al., 2024); however, making NLP models more sensitive to social factors could also make them a threat to privacy across social groups. The performance of machine learning approaches on tasks like author profiling could increase, resulting in a large potential for misuse, such as the following examples: (1) Author profiles could be used to identify and profile individuals or political dissenters

(Hovy and Spruit, 2016); (2) Author profiling could be used for predatory ad targeting, which might show gambling ads to vulnerable groups or not show job postings to certain social groups (Dudy et al., 2021); and (3) Author profiles could lead to data leakage, such as making health conditions recoverable for insurance companies that might increase their rates for certain individuals (Dudy et al., 2021).

This conflict between privacy and fairness has been described as one of the "dual-use problems" in NLP by Hovy and Spruit (2016). We aim to improve fairness without compromising individual privacy and safety but acknowledge that progress in one might sometimes come at the expense of the other. 📣 Therefore, we encourage researchers in the NLP community to engage with the dual-use problem more actively and work on techniques to make the design of language models more sensitive to human values, as suggested in Dudy et al. (2021), ideally without actively working on approaches to make sensitive data recoverable from texts. We further encourage researchers to actively anonymize datasets used for modeling and the evaluation of style representations.

We confirm that we have read and abide by the ACL Code of Ethics. Besides those mentioned, we do not foresee immediate risks of our work.

Acknowledgments

We thank the anonymous ARR reviewers for their constructive comments. Further, we thank Nicholas Andrews, Ana Lopes, Albert Gatt, Christoph Purschke and Jack Grieve for feedback on earlier drafts. We also thank our respective groups at Utrecht University and John Hopkins university for constructive discussions. Any remaining errors are our own.

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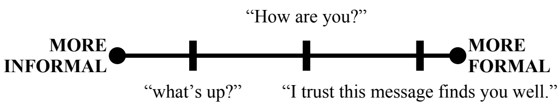

Figure 3: **Style is relative.** It might be more difficult or less interesting to make categorical judgments about a text’s style in isolation than, for example, judging if a text is more formal than another on a formality continuum. As Irvine (2001) writes on page 22, “It is seldom useful to examine a single style in isolation” and “attention must be directed to relationships among styles—to their contrasts, boundaries and commonalities.”

A Additional figures and tables

Fig. 4 provides a visual organization of the structure of this survey paper, Tab. 1 shows an overview of various predefined feature style operationalizations (§3.1), and Fig. 3 portrays an example of why style may require new solutions (§6).

B Motivating examples

B.1 Reasoning traces in the s1 dataset

We created Fig. 1 using the first 500 elements of the s1 datasets provided by Muennighoff et al. (2025) with reasoning traces generated by Gemini Flash Thinking Experimental and DeepSeek R1.[12] We used a semantic representation model[13] and a style representation model[14] and UMAP (McInnes et al., 2018) with default settings.

Pioneering work found that the style of reasoning traces might be important to consider for the performance of reasoning models (Lippmann and Yang, 2025). Note, however, that their definition of style does not fully align with the definition used in this paper (e.g., including “non-linear thinking” as a style). In an ablation, we compare the semantic and style representations of the DeepSeek and Gemini teacher models and the distilled Qwen models on DeepSeek and Gemini. While the original Muennighoff et al. (2025) paper trains Qwen models only on Gemini reasoning traces, the authors later experimented with DeepSeek reasoning traces and found them to lead to better performance.[15] We take the first 270 s1 reasoning traces as provided by Muennighoff et al. (2025) and use the fine-tuned Qwen models on Gemini[16] and DeepSeek[17] reasoning traces to generate reasoning traces[18] for the first 270 Math500[19] problems (Lightman et al., 2023). We use a different dataset from s1 to query student models to avoid artifacts of memorization. We choose Math500 as the distilled s1 Qwen models were also evaluated on it. See the results in Fig. 5 using UMAP visualization as before. We show that the style of the model distilled on Gemini reasoning traces is also closer in style to the Gemini reasoning traces than to the DeepSeek reasoning traces. Thus, the student model is effectively adopting the style of the teacher model (same for the DeepSeek model).

B.2 Rephrases of the MRPC dataset

Using synthetic data in pre- and post-training is increasingly common. We take the prompt from Maini et al. (2024) and use the Mistral-7B-Instruct-v0.1 model[20] (Jiang et al., 2023) to create

[12] “gemini_thinking_trajectory” and ‘deepseek_thinking_trajectory” column in `https://huggingface.co/datasets/simplescaling/s1K-1.1`

[13] Hugging Face’s sentence-transformers/all-mpnet-base-v2

[14] Hugging Face’s AnnaWegmann/Style-Embedding

[15] `https://x.com/Muennighoff/status/1886405528777073134`

[16] `https://huggingface.co/simplescaling/s1-32B`

[17] `https://huggingface.co/simplescaling/s1.1-32B`

[18] By preceding the response with “\n<|im_start|>think\n”

[19] `https://huggingface.co/datasets/HuggingFaceH4/MATH-500`

[20] `https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.1`

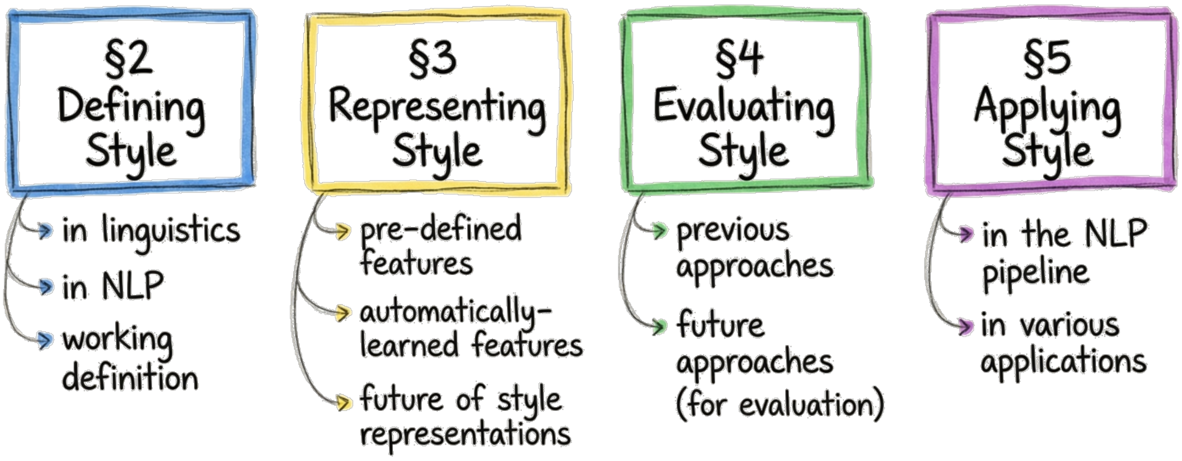

Figure 4: **Overview of the survey structure** This figure was digitalized from our own hand-drawn figure using NotebookLM and DALL-E. It keeps the same wording as the source material.

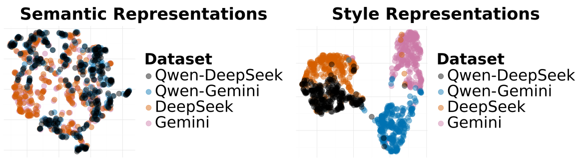

Figure 5: **Style representations of distilled Qwen models are close to teacher models** We compare reasoning traces on s1 for DeepSeek and Gemini models (Muennighoff et al., 2025) and reasoning traces on Math500 (Hendrycks et al., 2021) generated by models distilled on the s1 DeepSeek and Gemini reasoning traces respectively. The style representations (right) group the style of the student model closer to the style of the teacher model, while the semantic representations (left) overlap.

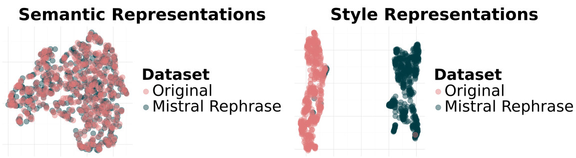

Figure 6: **Comparing semantic and style representations of LLM-rephrases** We compare MRPC sentences (Dolan and Brockett, 2005) and their LLM-generated "Wikipedia-style" rephrases using prompts from Maini et al. (2024). Style embedding models (right) can easily distinguish between the original and the LLM-rephrased sentences, while semantic embeddings (left) overlap. Studying stylistic diversity of LLM-rephrases is relevant as stylistic rephrasing is increasingly used in dataset curation for pre- and post-training.

Wikipedia-style rephrases of the first 500 elements of the MRPC dataset (Dolan and Brockett, 2005). We use the same models as in §B.1 for the semantic and style representations as well as hyperparameters for the UMAP visualization. Style representations clearly distinguish the LLM rephrases from the original sentences, while semantic representations do not (Fig. 6).

B.3 Clustering writers of English by native language

We created Fig. 2 using the ETS Corpus of Non-Native Written English (LDC2014T06) (Blanchard et al., 2014). The corpus is comprised of English essays written by speakers of 11 non-English native languages as part of an international test of academic English proficiency, TOEFL (Test of English as a Foreign Language). We used LUAR[21] (Rivera Soto et al., 2021), a style representation model trained on the authorship verification task. Each point in the figure is an embedding of 5 TOEFL essays written by authors of the same native language picked at random. We reduce the dimensionality to two components using UMAP (McInnes et al., 2018) with default settings. Although the style representation was initially trained on the "idiolectal" authorship verification task (distinguishing authors based on their distinctive language use), Fig. 2 reveals that it also captures features indicative of the writer's native language.

[21] https://huggingface.co/rrivera1849/LUAR-MUD

C Additions to style conceptualizations

Fully separating style and semantic meaning might be impossible.

> *Sociolinguists generally think of styles as different ways of saying the same thing. In every field that studies style seriously, however, this is not so.*
>
> — Penelope Eckert

A precise separation of semantic meaning and style poses practical challenges. It has been argued that, for example, only Labov (1972)'s original object of study—phonological variables—can leave semantic meaning untouched, whereas all other variables, including lexical and syntactic variables, will necessarily change the semantic meaning (Campbell-Kibler, 2011; Lavandera, 1978; Sun et al., 2023). Additionally, Eckert (2008, 2012) argues that using a certain style systematically connects an utterance to the social world, and that style thus influences social meaning. Others argue that any two forms must necessarily contrast in meaning (Clark, 1992). Some work in sociolinguistics sidesteps the problem of meaning equivalence by identifying and studying the contexts in which a set of linguistic forms are alternants without claiming equivalence (Campbell-Kibler, 2011; Christensen and Jensen, 2022). Nonetheless, we believe that attempting to separate style and semantic meaning has practical uses (see §2.2 or Weiner and Labov (1983)).

Style across research fields Several fields study linguistic style in some capacity. As discussed in the paper, *sociolinguistics* examines the relationship between language and society with a focus on language change and variation (Eckert, 2008; Labov, 1972). *Corpus linguistics* is the descriptive study of how language is actually used by analyzing text corpora (e.g. Biber, 1988; Biber and Conrad, 2019). Typical applications might include comparing language between different genres like scientific papers and news articles. *Forensic linguistics* involves the study of style in the context of law and crime investigation and is typically interested in recognizing a style or *idiolect* that helps distinguish an investigated individual (Coulthard, 2004). Practical insights from forensic linguistics also reciprocally influence *stylistics* and *stylometry*, which more generally study linguistic style in language. Stylometry applications include investigating the style of literary authors (Holmes, 1985) or attributing disputed literary works (Burrows, 2002; Mosteller and Wallace, 1963; Stamatatos, 2009). Style in *NLP* has been investigated to characterize authors (e.g., age or gender in Koppel et al., 2002; Nguyen et al., 2013), detect stylistic inconsistencies (Collins et al., 2004; Stamatatos, 2009), and adapt styles in machine translation (Niu et al., 2017, 2018; Rabinovich et al., 2017). Linguistic style also plays a significant role in related fields like *psycholinguistics*, or even in *communication* and *marketing*, such as by influencing consumer engagement (Munaro et al., 2024; ShabbirHusain et al., 2023) and purchases (Ludwig et al., 2013).

Note that these fields are not strictly separable. Methods from corpus linguistics can inform sociolinguistics, forensic linguistics can use methods from stylometry, and so on. Further, there are several fields that can be connected to linguistic style that we do not specifically discuss here, such as *discourse analysis*, *digital humanities*, *linguistic anthropology*, and *sociology*.

D Additions to representing style in NLP

Available predefined feature extraction tools There are a multitude of tools available that automatically extract predefined features from text. The choice of tool and feature set, though, depends on various factors, such as preferred programming language, the nature of the data, and the goal of the task. Therefore, best practice is to systematically compare multiple feature sets, sometimes across tools, for each specific use case. Python tools include but are not limited to spaCy (Honnibal et al., 2020), Stanza (Qi et al., 2020), and NLTK (Bird et al., 2019) for general text processing, PAN submissions for authorship attribution (Weerasinghe and Greenstadt, 2020) and style change detection tasks (Strøm (2021), Zlatkova et al. (2018), LFTK (Lee and Lee, 2023) for extracting numerous stylometric features (but not n-grams), NeuroBiber and BiberPlus (Alkiek et al., 2025) for extracting Biber-style features, and StyloSpeaker (Aggazzotti and Smith, 2025) for extracting speech transcript features. Non-Python stylometric authorship tools include Stylo in R (Eder et al., 2016) and JStylo in Java (PSAL, 2013). Software that does not require programming includes LIWC (Pennebaker et al., 2015), which groups words into linguistically and psychologically meaningful categories; JGAAP (Juola et al., 2009) and Signature (Millican, 2003), which extract stylometric and n-gram features; and Coh-Metrix, which can measure more complex features like text cohesion (Graesser et al., 2004). We summarize these tools in Tab. 2.

Available automatically-learned models To the best of our knowledge, the available learned style representation models on HuggingFace are CISR[22] (Wegmann et al., 2022), StyleDistance[23] (Patel et al., 2025), mStyleDistance[24] (Qiu et al., 2025), LUAR[25] (Rivera Soto et al., 2021) and Multilingual Style Representation[26] (Kim et al., 2025). Another model available via a private sharing site is LISA[27] (Patel et al., 2023). Following the discussion in §3.2, some style representations may capture more semantic features than others, and thus may prove to be more useful for different downstream tasks. We summarize these models in Tab. 3.

D.1 Additions to the future of style representations

❓ Automatic feature selection

Future work could attempt to create strategies to select predefined features that work best for different kinds of data and objects of study or develop an ensemble method that can select the best features dynamically.

❓ Including language modeling objectives

Previous work found that fine-tuning pretrained transformer models on style tasks can curiously lead to reduced performance on some style tasks compared to the pretrained base model (Patel et al., 2024; Wegmann and Nguyen, 2021). This might be connected to a difference in the object of study for the training and evaluation tasks. For example, using individuals as the object of study (e.g., using authorship verification as the training task) can lead to unlearning stylistic attributes that can vary for the same individual (e.g., the formality of their writing across online forums, job applications, and other contexts). When aiming to learn general-purpose style representations, it might be necessary to include further stylistic or continued language modeling objectives like masked language modeling.

[22] https://huggingface.co/AnnaWegmann/Style-Embedding

[23] https://huggingface.co/StyleDistance/styledistance

[24] https://huggingface.co/StyleDistance/mstyledistance

[25] https://huggingface.co/rrivera1849/LUAR-MUD

[26] https://huggingface.co/Blablablab/multilingual-style-representation-Llama-3.2

[27] https://ajayp.app/posts/2023/11/learning-interpretable-embeddings-via-llms/

❓ Improve content-independence

This was already mentioned in the main paper, but we highlight this point for more clarity again. "Generally, few style representations reach high scores on content-independence (🔧 App. Tab. 3) and might benefit from more exhaustive content disentanglement.", see §4.1. Consider current content-disentanglement strategies in §3.2.

E Additions to evaluating style representations

Leverage measurement theory We give some concrete examples of how measurement theory (🔧 see Trochim et al., 2015) might be applied for style embeddings and benchmarks. Measurement theory can provide a theoretical framework that helps make sure different important validity and reliability aspects are considered in the evaluation of style representations and style benchmarks.

For style embeddings, *convergent validity* (i.e., does the measure show similar measurement for similar concepts?) might be assessed by testing that texts that have a similar style have similar representations. This could be done by perturbing texts in stylistically inconsequential ways (e.g., by swapping out named entities like "Maria has style." to "Emma has style.") and comparing their embeddings. *Discriminant validity* (i.e., Is the measure not sensitive to concepts it should not be related to?) might be assessed by confirming that texts that change in other aspects than style (e.g., content) are still embedded similarly. This has been assessed before by evaluating content-independence (§4). *Predictive validity* (i.e., Can the measure be used to predict something that it should be predictive of?) might be assessed by evaluating performance on downstream tasks that make use of style representations, such as style classification or style transfer tasks (§4). 🔧 See also Fang et al. (2022) for further inspiration.

For style benchmarks, *reliability* (i.e., Is the measure giving the same results with repeated measurement?) might be improved by making sure that the same seeds are used when applying the benchmarks—for example, when using style classification tasks and a classifier is trained on top of embeddings. 🔧 See also Bean et al. (2025) for further inspiration related to benchmark *validity*—for example, they suggest to employ sampling strategies like stratified sampling that are representative of the task space.

F Additions to what style representations can enable

Disentangle internal representations It may be useful to disentangle LLM-internal representations of style to allow models to turn style information on or off as needed. Disentanglement approaches have helped cross-domain generalization (Yang et al., 2023; Zheng and Lapata, 2022) and might also help cross-style generalization. This can be especially relevant for stylistic tasks (e.g., machine text detection) that should rely on, and for semantic tasks (e.g., reasoning) that should not rely on, style information (Wegmann et al., 2025). Disentanglement might work especially well with mixture-of-experts approaches (Artetxe et al., 2022), with style-specific architectures (e.g., tokenizers) for relevant experts.

Authorship attribution Style representations can enable authorship verification and attribution tasks, including historical authorship attribution of disputed texts (Mosteller and Wallace, 1963), identifying harmful actors (Arabnezhad et al., 2020; Saxena et al., 2025), detecting plagiarism in educational contexts (Elkhatat et al., 2023), and attributing speakers from speech transcripts (Aggazzotti et al., 2024, 2025b; Tripto et al., 2023).

Considering style in annotations Human-written texts and labels can include spurious correlations as a result of annotation instructions (Gururangan et al., 2018). Style representations could be used to monitor the output of annotation efforts, and ultimately, to distinguish instructions that evoke more stylistically diverse annotations.

Bias identification and reduction As mentioned (§ 1), language models are often biased against certain styles, including those associated with marginalized groups. Approaches detailed in §5.1, like curating training and evaluation datasets with more diverse styles, can improve performance across styles and thus reduce model bias. Further, it might be possible to use style representations to identify biased behavior of a trained model: For example, representations might be used to generate (§5.2) or cluster texts of similar styles, enabling systematic comparisons of model performances across style clusters.

Develop style measures With style measures we mean the broader class of methods and metrics that include style representations. One might, for example, develop a metric that measures the formality of a text, returning values between 0 and 1. Style representations are similarly quantitative measures of stylistic properties, but they typically encode (latent) stylistic dimensions in a vector space. In this study, we focus on style representations, but they can be applied to develop style metrics.

F.1 Open questions in the application of style representations

We add open challenges in the application of style representations to different problems.

Circular evaluation in style transfer When performing generative tasks conditioned on style representations, such as authorship style transfer, difficulties can arise when comparing models. Various works (Horvitz et al., 2024a,b; Khan et al., 2024) train authorship style transfer models with the aid of style embedding models (§3.2) but also evaluate the adherence to the target style using style embedding models. When comparing two systems like ParaGuide (Horvitz et al., 2024a) and StyleMC (Khan et al., 2024), the former trained with CISR embeddings (Wegmann et al., 2022) and the latter with LUAR embeddings (Rivera Soto et al., 2021), it remains unclear which embedding space to use for evaluation without giving either model undue advantage. We encourage the community to investigate additional possibilities for evaluation (e.g., based on predefined features, cf. §4.1) or establish a standard representation for training as well as evaluation.

Should we even care about styles for user-facing LLMs? Some recent work shows that more human-like outputs by LLMs might be dispreferred by humans and might lead to increased anthropomorphism (Cheng et al., 2025; Sandoval et al., 2025). This hints at a complex set of desiderata NLP researchers should consider when building LLMs and when using representations to steer LLMs toward generating texts in different styles. However, what style of output is preferred remains highly contextual (i.e., dependent on the setting) (Sandoval et al., 2025), and we believe that training on stylistically diverse corpora remains essential for LLMs to understand and engage with diverse human styles.

G Intended use and licenses for used artifacts

We only use models and datasets for motivating examples in our survey. We discuss their licenses and intended use below.

G.1 Datasets

s1k We use the s1k dataset provided by Muennighoff et al. (2025) and accessed at https://huggingface.co/datasets/simplescaling/s1K-1.1. The dataset was shared with an MIT license, which we adhere to.

MRPC We use the MRPC dataset provided by Dolan and Brockett (2005). The dataset is available on the Microsoft website at https://www.microsoft.com/en-us/download/details.aspx?id=52398. No license information is easily available. However, it is a widely used and shared dataset, and the paper mentions it is for the express purpose of stimulating research.

Math500 We use the Math500 dataset provided by Lightman et al. (2023). It was shared with an MIT license by OpenAI. See https://github.com/openai/prm800k/.

ETS Corpus of Non-Native Written English We use the ETS Corpus of Non-Native Written English (also known as TOEFL11 or LDC2014T06) provided by Blanchard et al. (2014). It is accessed via the Linguistic Data Consortium (LDC) at https://catalog.ldc.upenn.edu/LDC2014T06. The dataset is distributed under a specific LDC user license agreement restricted to non-commercial research use, which we adhere to.

G.2 Models

CISR We use Wegmann et al. (2022)'s CISR model at https://huggingface.co/AnnaWegmann/Style-Embedding. No clear license information is given, but the model was published in a research paper encouraging further use.

LUAR We use Rivera Soto et al. (2021)'s LUAR model at https://huggingface.co/rrivera1849/LUAR-MUD, shared with an Apache 2.0 license, which we adhere to.

SBERT We use an SBERT (Reimers and Gurevych, 2019) semantic representation model, https://huggingface.co/sentence-transformers/all-mpnet-base-v2, shared with an Apache 2.0 license, which we adhere to.

Mistral We use Jiang et al. (2023)'s Mistral-7B-Instruct-v0.1 model, https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.1. The model was shared with an Apache 2.0 license, which we adhere to.

s1 models We use Muennighoff et al. (2025)'s fine-tuned Qwen models on Gemini (https://huggingface.co/simplescaling/s1-32B) and DeepSeek (https://huggingface.co/simplescaling/s1.1-32B). Both models are shared with an Apache 2.0 license, which we adhere to.

H Identifying or offensive content in datasets

We use small existing datasets only for motivating examples (see §B). We do not release datasets. We do not expect the used datasets (§G.1) to include offensive content as they are reasoning datasets, crowd-worker created paraphrases and TOEFL essays. However, the TOEFL essays might include some personally identifying content. We did not take steps to remove identifiable cues or offensive content. We hope that the effect is negligible as the datasets were already publicly accessible and we only use them as motivating examples.

I Use of AI Assistants

We used ChatGPT, GitHub Copilot, and Claude Code for coding, to look up commands, and to generate individual functions for plotting. Generated functions were tested w.r.t. expected behavior. We used AI assistants (mostly Claude and ChatGPT) for concise rephrasing and grammatical error correction in writing. We used NotebookLM and DALL-E to generate one figure based on specific instructions including exact wording (see Appendix Fig. 4).

Type	Variable	Examples
PHONETIC	postvocalic /r/	more or less clear pronunciation of /r/ sound after vowel (Labov, 1972)
	intervocalic /t/	full/flapped /t/ voicing between two vowel sounds (*writer* → *rider*) (Bell, 1984)
	...	
MORPHO-LOGICAL	word endings	*g*-dropping (Campbell-Kibler, 2007), gerunds (Biber, 1988)
	nominalizations	ending in *-tion*, *-ment*
	verb morphology	*be* as a main or auxillary verb (Biber, 1988)
	...	
LEXICAL	word/token counts	number of words/tokens (Stamatatos, 2009)
	word/token ratios	ratio of types to tokens, ratio of short/long words to token count, etc. (Altakrori et al., 2021)
	word/token n-grams	for n of various lengths (Abbasi and Chen, 2008; Stamatatos, 2009)
	word length	average word length (Biber, 1988), also cf. Grieve (2007)
	sentence length	distribution of average sentence length, cf. Grieve (2007)
	vocabulary richness	hapax (dis)legomena, Yule's I/K, number of unique tokens (Abbasi and Chen, 2008; Stamatatos, 2009)
	function words	grammar-functioning words, e.g., *the*, *be*, *to* (Abbasi and Chen, 2008; Mosteller and Wallace, 1963; Stamatatos, 2009)
	pronoun use	word frequency distributions of 1st, 2nd,... person pronouns (Biber, 1988; Pennebaker et al., 2015)
	hedge words	*at about*, *something like* as hedges in Biber MDA features; *maybe*, *perhaps* in tentative dimension in LIWC
	quantifiers	*each*, *all* as quantifier words or *everybody*, *anybody* as quantifier pronouns (Biber, 1988)
	...	
SYNTACTIC	POS counts	noun, verb, adjective,... (Abbasi and Chen, 2008; Biber, 1988)
	POS n-grams	for various n (Abbasi and Chen, 2008; Weerasinghe and Greenstadt, 2020)
	passive voice	agentless passives (Biber, 1988)
	subordination features	*that* relative clause vs. *wh-* relative clause (e.g., *the dog that* vs. *the dog who*) (Biber, 1988)
	negation	*need no water* as negative concord (Eckert, 2008); *not* in analytic negation (Biber, 1988), negation words in LIWC
	invariant *be*	*He be working* (Rickford and McNair-Knox, 1994)
	zero copula	*She nice* (Rickford and McNair-Knox, 1994)
	...	
DISCOURSE	contraction use	*can't* vs. *cannot* (contractions list[1] Biber (1988))
	discourse particle	*well*, *now* (Biber, 1988)
	readability	Flesch Reading Ease, Flesch Kincaid Grade Level, etc. (Python's `textstat`[2])
	compression	train a compression model on one text and use it to estimate how similar in style another text is, cf. Stamatatos (2009)
	...	
ORTHO-GRAPHIC	character types	hashtags, emojis, exclamation marks (Clarke and Grieve, 2017); uppercase characters, digits (Stamatatos, 2009)
	character n-grams	for various n (Abbasi and Chen, 2008; Stamatatos, 2009)
	lengthening	*cooool* (Nguyen and Grieve, 2020)
	number substitutions	*2day* (Crystal, 2008)
	misspellings	common misspellings list[3]
	acronyms/abbreviations	common shortened forms list[4]
	...	

[1] `https://en.wikipedia.org/wiki/Wikipedia:List_of_English_contractions`
[2] `https://pypi.org/project/textstat/`
[3] `https://en.wikipedia.org/wiki/Wikipedia:Lists_of_common_misspellings/For_machines`
[4] `https://en.wikipedia.org/wiki/SMS_language`

Table 1: **Overview of predefined feature style operationalizations used in different fields.** Specific linguistic features that have been used to operationalize style and examples of each are categorized by linguistic level: phonetic (i.e., pronunciation and sound patterns), morphological (i.e., word structure and inflection), lexical (i.e., word choice), syntactic (i.e., sentence structure), discourse (i.e., larger structure), and orthographic (i.e., spelling and punctuation). Note that the categorizations might overlap, e.g., *g*-dropping might also be considered an orthographic or phonological variable, and character n-grams might encode different morphemes. These features have been investigated separately (Campbell-Kibler, 2009) and collectively (e.g., Abbasi and Chen, 2008; Biber, 1988; Neal et al., 2017; Stamatatos, 2009). This table was inspired by and partially filled with elements from other tables of stylometric features in these and other sources. For further references and examples consider also Grieve (2007) and Biber (1988).

Tool	Original Purpose	Language / Platform	Type	Link
spaCy (Honnibal et al., 2020)	General text processing	Python	library	github.com/explosion/spaCy
Stanza (Qi et al., 2020)	General text processing	Python	library	https://github.com/stanfordnlp/stanza
NLTK (Bird et al., 2019)	General text processing	Python	library	github.com/nltk/nltk
PAN 2020 AV (Weerasinghe and Greenstadt, 2020)	AV	Python	Task subm.	github.com/janithnw/pan2020_authorship_verification
PAN 2021 SCD (Strøm, 2021)	SCD	Python	Task subm.	github.com/eivistr/pan21-style-change-detection-stacking-ensemble
PAN 2019 SCD (Zuo et al., 2019)	SCD	Python	Task subm.	github.com/chzuo/PAN_2019
PAN 2018 SCD (Zlatkova et al., 2018)	SCD	Python	Task subm.	github.com/machinelearning-su/style-change-detection
LFTK (Lee and Lee, 2023)	Stylometric feature extraction (no n-grams)	Python	library	github.com/brucewlee/lftk
BiberPlus (Alkiek et al., 2025)	Biber-style feature extraction	Python	library	github.com/davidjurgens/biberplus
NeuroBiber (Alkiek et al., 2025)	Biber-style feature extraction	HF	Model	huggingface.co/Blablablab/neurobiber
MAT (Nini, 2019)	Biber-style feature extraction	Python	library	github.com/andreanini/multidimensionalanalysistagger
StyloSpeaker (Aggazzotti and Smith, 2025)	Speech transcript feature extraction	Python	library	github.com/caggazzotti/styloSpeaker
Stylo (R) (Eder et al., 2016)	Stylometric authorship analysis	R	library	github.com/computationalstylistics/stylo
JStylo (Java) (PSAL, 2013)	Stylometric authorship analysis	Java	App	github.com/psal/jstylo
LIWC (Pennebaker et al., 2015)	Ling./psych. categories	SW (GUI)	App	www.liwc.app/
JGAAP (Juola et al., 2009)	Stylometric + n-gram features	SW (GUI)	App	evllabs.github.io/JGAAP/
Signature (Millican, 2003)	Stylometric + n-gram features	SW (GUI)	App	www.philocomp.net/texts/signature.htm
Coh-Metrix (Graesser et al., 2004)	Text cohesion and discourse features	SW (GUI)	App	soletlab.asu.edu/coh-metrix/

Table 2: **Comparison of common tools for extracting predefined features** The table summarizes their original purpose, programming language or platform, type of resource, and URL. Abbreviations: **AV** = authorship verification, **Task subm.** = shared-task submission, **SCD** = style change detection, **HF** = Hugging Face, **App** = standalone application, **SW** = non-programming software. These tools particularly work for English, but see our Github for tools/papers for other languages: https://huggingface.co/AnnaWegmann/Style-Embedding.

Model	Training Task	Languages	Content / Style Disentanglement	Interpretable?	Tasks
LUAR	AV	English	Weak	No	AR, MTD
CISR	AV	English	Medium	No	AV, MTD
StyleDistance	AV	English	Strong	No	AV, ST
mStyleDistance	AV	Multiple	Strong	No	AV, ST
LISA	AV	English	Strong	Yes	Unknown
Multilingual Style	AV	Multiple	Medium	No	AR, MTD

Table 3: **Comparison of open-source learned style representation models** The categorization is based on key dimensions including the languages supported, the measured strength of content/style disentanglement, interpretability, and the specific downstream tasks the models are have been found useful for. Note that the models may be useful for more tasks than stated here, the analysis is based on the authors' experience with them. Acronym Definitions: **AR** = Authorship Retrieval, **AV** = Authorship Verification, **MTD** = Machine-Text Detection, **ST** = Style Transfer