Token-Wise Kernels (TWiKers) for Vicinity-Aware Attention in Transformers

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Abstract

Self-attention mechanisms in transformers enable tokens to interact across a sequence but lack an explicit inductive bias to capture local contextual dependencies, an inherent characteristic of human languages. We propose Token-Wise Kernels (`TWiKers`), a novel enhancement to transformers that learn token-specific convolutional kernels applied to the keys or values. Each token is assigned a small kernel, initialized to the "Central Dirac" (e.g., [0,1,0] for size=3), meaning the token "bears" the attention from all other tokens alone. During training, these kernels adapt, and greater deviation from the Central Dirac indicates stronger attention redistribution to neighboring tokens. This introduces the first transformer weights with direct semantic interpretability. Our experiments show that content words (e.g., nouns and verbs) retain self-focus, while function words (e.g., prepositions and conjunctions) shift attention toward their neighbors, aligning with their syntactic and semantic roles. We further apply `TWiKers` to distinguish literary genres, historical periods, and authors, demonstrating their effectiveness in capturing high-level stylistic patterns. Finally, by allowing them to vary with attention heads, we show the potential of `TWiKers` as a new inductive bias to enhance transformer training.

1 Introduction

Transformers have revolutionized natural language processing (NLP), powering large language models (LLMs) that achieve state-of-the-art performance across diverse tasks. Recent base models, such as DeepSeek-V3 (DeepSeek-AI et al., 2025), LLaMA-4 (Grattafiori et al., 2024), and Qwen-3 (Yang et al., 2025), have exhibited increasingly strong emergent abilities, fueling speculation that large language models may be approaching the threshold of artificial general intelligence (AGI).

One of the most remarkable aspects of transformers is the multi-head attention mechanism (Vaswani et al., 2017), which not only offers scalability but also enhances interpretability. Deep embeddings facilitate distance-based comparisons, a fundamental principle behind retrieval-augmented generation (RAG) (Lewis et al., 2020)–a key ingredient of modern AI agents. Token (shallow) embeddings are also widely used for lexical analysis, including clustering (Cha et al., 2017; Zhang et al., 2023), visualization (Le and Lauw, 2017; Molino et al., 2019), and analogy reasoning (Zhu et al., 2018; Petersen and van der Plas, 2023). However, these embeddings lack inherent meaning on their own; their interpretability depends on distance measurements and comparisons. So far, *no weights in transformers have been shown to encode direct semantic meaning at the parameter level.*

While one strength of transformers is their ability to capture long-range contextual dependencies, human languages exhibit strong vicinity reliance, particularly at the lexical level. For example, when reading *"War and Peace"*, a human would naturally focus on *"War"* and *"Peace"* while ignoring *"and"*, which carries less semantic weight. This selective attention to content words over function words is a fundamental characteristic of natural language, not unique to English but observed in most languages. Such locality has supported sliding-window attention, enabling models like Longformer (Beltagy et al., 2020) to achieve linear-time attention computation, along with its variations such as BigBird (Zaheer et al., 2020), Mamba (Gu and Dao, 2024), and LongLoRA (Chen et al., 2024). In computer vision, similar principles have been applied in models like Swin Transformer (Liu et al., 2021) and Neighborhood Attention Transformer (NAT) (Hassani et al., 2022). Another approach that exploits local dependencies is n-gram tokenization, which explicitly captures fixed-length word sequences (Mikolov et al., 2013b; Pennington et al., 2014; Bojanowski et al., 2017; Devlin et al., 2019). However, *despite the prevalence of local dependencies in hu-*

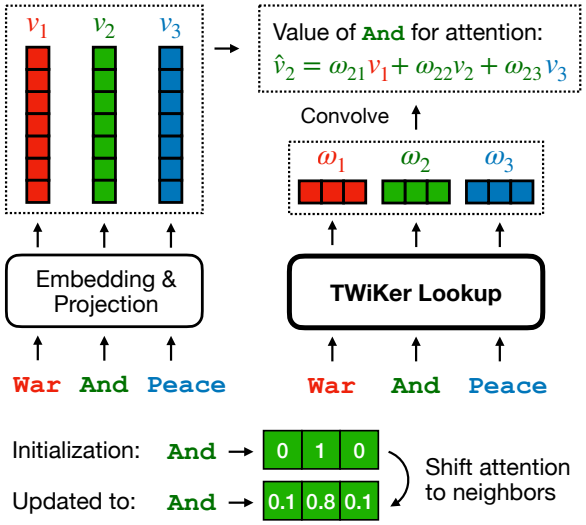


Figure 1: Overview of the TWiKer mechanism. After training, ω deviating from the Central Dirac ([0,1,0]) indicates a shift in attention toward neighboring tokens. Here we omit TWiKers for keys and their variability across heads for simplicity.

man languages, the transformer architecture lacks an explicit inductive bias to take advantage of this characteristic.

In this paper, we introduce **Token-Wise Kernels (TWiKers)**, a novel enhancement to transformers that incorporates an inductive bias to reflect vicinity reliance while preserving transformer's global attention. We assign a small, trainable convolutional kernel to each token, enabling the model to learn how different tokens interact with their immediate neighbors through attention redistribution. In this way, TWiKers capture vicinity-aware semantic relationships, as illustrated in Figure 1.

The key novelties of TWiKers are as follows:

1. **Direct Semantic Meaning**: Unlike standard transformer weights, TWiKers learn interpretable patterns that align with syntactic and semantic roles of words. For example, content words (nouns, verbs) tend to retain self-focus, while function words (e.g., prepositions, conjunctions) emphasize their surroundings.

2. **Automatic Lexical and Semantic Analysis**: Since TWiKers encode token-specific contextual behavior, they can be directly analyzed to distinguish lexical categories, track historical language changes, and classify text styles without additional supervision.

3. **Enhanced Training Efficiency**: Given its semantic relevance, TWiKers provide a meaningful inductive bias that may improve both pretraining and finetuning by helping transformers learn embeddings aligning better with human languages.

We validate TWiKers through comprehensive experiments for English, demonstrating their alignment with linguistic principles and their effectiveness in real-world applications.

2 Related Work

2.1 Sliding-Window Attention

To address the quadratic complexity of full self-attention, the sliding-window methods confine attention to local regions. For example, Longformer (Beltagy et al., 2020) uses fixed-size local windows with select global tokens for linear complexity, while BigBird (Zaheer et al., 2020) integrates random and sparse global patterns to better approximate full attention. Recent methods like Mamba (Gu and Dao, 2024), LongLoRA (Chen et al., 2024), BASED (Arora et al., 2024), and CEPE (Yen et al., 2024) further optimize local attention. In computer vision, approaches such as Swin Transformer (Liu et al., 2021) and NAT (Hassani et al., 2022) similarly enhance efficiency by focusing attention on local regions.

Although sliding-window approaches resemble TWiKers in their emphasis on local context, their motivations and effects fundamentally differ. Sliding-window methods aim to improve efficiency by restricting attention to fixed-size windows, thereby compromising the transformer's global receptive field. In contrast, TWiKers explicitly encode local semantic interactions into token-level parameters, enabling the model to capture local dependencies without sacrificing global attention. Nonetheless, both approaches are grounded in the vicinity-dominated nature of human languages.

2.2 N-Gram Tokenization

N-gram tokenization, also based on strong vicinity reliance, represents language as sequences of contiguous units. Traditional n-gram models–often enhanced by smoothing techniques such as Kneser-Ney (Kneser and Ney, 1995)–have demonstrated effectiveness in classical language modeling. Neural approaches further incorporate n-gram features: fastText (Bojanowski et al., 2017) enriches word embeddings with character-level n-grams, while BPE (Sennrich et al., 2016) and SentencePiece (Kudo and Richardson, 2018) construct

subword vocabularies based on frequent n-gram patterns. Recent developments have extended the power of n-gram modeling. N-Grammer (Thai et al., 2020) augments transformers by integrating latent n-gram representations directly into the architecture. Subsequent analytical work has employed n-gram statistics to examine how language models implicitly capture linguistic structures (Li et al., 2022), conceptually close to our methodology. The Infini-gram model (Liu et al., 2024) generalizes n-gram methods to infinite-length sequences using an advanced back-off mechanism. Again, n-gram tokenizers highlight the strong local dependencies in natural language, which modern subword tokenizers under-exploit. This principle aligns with our approach. However, `TWiKers` capture locality through adaptive, semantically meaningful weights learned directly from data.

2.3 Token Embeddings in NLP Tasks

Token embeddings are shallow representations of tokens. While they are less effective than deep transformer embeddings for contextual understanding, they have proven valuable in lexical semantic studies. Foundational models such as LSA (Landauer and Dumais, 1997), word2vec (Mikolov et al., 2013b), GloVe (Pennington et al., 2014), and fastText (Bojanowski et al., 2017) laid the groundwork for applications including clustering (Hill et al., 2015; Vulić and Mrkšić, 2018), visualization (Mikolov et al., 2013a; Reif et al., 2019), and analogy reasoning (Mikolov et al., 2013b). Recent work has extended these embeddings to cognitive and psycholinguistic domains, where they are used to model human semantic memory, word associations, and lexical access (Günther et al., 2019; Nematzadeh et al., 2017; Chronis and Erk, 2020; Samir et al., 2020). However, existing token embeddings are largely derived from statistical co-occurrence and offer limited semantic interpretability via distance comparison. In contrast, `TWiKers` provide direct semantic interpretability, distinguishing lexical categories (e.g., content vs. function words) and enabling automatic, linguistically meaningful analysis without supervision.

3 Methodology

3.1 Token-Wise Kernels in Self-Attention

In a standard transformer architecture (Vaswani et al., 2017), the attention mechanism computes output representations using the scaled dot-product attention:

$$A = \text{softmax}\left(\frac{\boldsymbol{Q}\boldsymbol{K}^\top}{\sqrt{d}}\right)\boldsymbol{V}, \tag{1}$$

where $\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V} \in \mathbb{R}^{L\times d}$, with L being the sequence length and d the feature dimension (ignoring the multi-head dimension). It allows each token to attend to all others in the sequence simultaneously, capturing global dependencies.

To introduce an explicit inductive bias for vicinity awareness while preserving global dependencies, we associate each token in the vocabulary with two kernels of size n: a key kernel $\boldsymbol{\omega}^{\text{k}} \in \mathbb{R}^n$ and a value kernel $\boldsymbol{\omega}^{\text{v}} \in \mathbb{R}^n$. These kernels modify the attention mechanism by convolving the keys and values with the kernels:

$$A = \text{softmax}\left(\frac{\boldsymbol{Q}(\boldsymbol{\Omega}^{\text{k}}\boldsymbol{K})^\top}{\sqrt{d}}\right)(\boldsymbol{\Omega}^{\text{v}}\boldsymbol{V}), \tag{2}$$

where $\boldsymbol{\Omega}^{\text{k}}, \boldsymbol{\Omega}^{\text{v}} \in \mathbb{R}^{L\times L}$ are banded matrices (with a fixed bandwidth of n) that assemble the per-token kernels ω^{k}_{ij} and ω^{v}_{ij} ($i = 1, 2, \ldots, L; j = 1, 2, \ldots, n$) in a sliding-window manner. For example, when $L = 4$ and $n = 3$:

$$\boldsymbol{\Omega}^{\text{k}} = \begin{bmatrix} \cancel{\omega^{\text{k}}_{11}} & \omega^{\text{k}}_{12} & \omega^{\text{k}}_{13} & & \\ \omega^{\text{k}}_{21} & \omega^{\text{k}}_{22} & \omega^{\text{k}}_{23} & & \\ & \omega^{\text{k}}_{31} & \omega^{\text{k}}_{32} & \omega^{\text{k}}_{33} & \\ & & \omega^{\text{k}}_{41} & \omega^{\text{k}}_{42} & \cancel{\omega^{\text{k}}_{43}} \end{bmatrix}. \tag{3}$$

Here, ω^{k}_{11} and ω^{k}_{43} are truncated at sequence boundaries to avoid padding. The value transformation matrix $\boldsymbol{\Omega}^{\text{v}}$ is assembled in the same manner. Equation (2) is provided here for clarity, while in practice, we adopt the standard fold-multiplication-unfold pipeline to preserve the $\mathcal{O}(L)$ complexity of convolution.

Understanding the semantic significance of key convolution ($\boldsymbol{\Omega}^{\text{k}}\boldsymbol{K}$) and value convolution ($\boldsymbol{\Omega}^{\text{k}}\boldsymbol{V}$) is essential for interpreting the learned weights. Key convolution directly shifts attention weights by incorporating neighboring tokens' key representations, effectively redistributing attention to surrounding words. Value convolution, on the other hand, blends local context into the retrieved representations, allowing tokens to reflect semantic nuances from nearby tokens. Together, these mechanisms enhance the model's ability to encode syntactic relationships and contextual meaning, explicitly reinforcing the importance of local dependencies in natural language understanding. Notably, these

vicinity-aware behaviors are semantically meaningful *only because the kernels are token-specific*, rather than position-based, distinguishing TWiKers from any position-wise parameters, such as IA3 for parameter-efficient finetuning (Liu et al., 2022).

3.2 Enforcing Causality

In autoregressive language modeling, tokens must not attend to future tokens (Vaswani et al., 2017; Dai et al., 2019). However, Eq. (2) introduces information leakage, as TWiKers allow the i-th token to incorporate key representations from up to $(n-1)/2$ future tokens, violating causality.

To address this, we must restrict the range of key and value summation in Eq. (2). The attention weight, $\boldsymbol{A} = \boldsymbol{Q}(\boldsymbol{\Omega}^{\mathrm{k}}\boldsymbol{K})^\top$, is corrected to:

$$A_{ij} = \sum_{l=1}^{d} Q_{il} \sum_{m=1}^{\min(n,p+i-j)} \omega^{\mathrm{k}}_{jm} K_{j-p+m,l} \quad (4)$$

where $p = (n+1)/2$. The upper bound of the inner summation is reduced from n (i.e., not considering leakage) to $\min(n, p+i-j)$, ensuring that query i only attends to past and present keys. In implementation, we only correct the affected main diagonal and the first $p-2$ sub-diagonals in A_{ij}, ensuring an $\mathcal{O}(L)$ complexity. The attention output is adjusted similarly by modifying the summation limits on value aggregation.

The corrections to the attention weights and output incur minimal overhead. However, they prevent TWiKer-based attention from being seamlessly compatible with KV caching and flash attention (Dao et al., 2022). While adapting TWiKers to these optimizations is feasible in principle, we omit such integration in our implementation, as TWiKers are applied only to the input layer. KV caching and flash attention remain fully applicable to all deeper layers.

3.3 Enforcing Probabilistic TWiKers

To enhance the interpretability of TWiKers, we enforce them to be probabilistic distributions, ensuring that their values are non-negative and sum to one. For this purpose, we define the unconstrained trainable parameters $\hat{\boldsymbol{\omega}}^{\mathrm{k}}$ and $\hat{\boldsymbol{\omega}}^{\mathrm{v}}$, which are transformed via a softmax function to compute the actual kernels used for convolution:

$$\omega^{\mathrm{k,v}}_{ij} = \frac{\exp\left(\hat{\omega}^{\mathrm{k,v}}_{ij}/\tau\right)}{\sum_{m=1}^{n}\exp\left(\hat{\omega}^{\mathrm{k,v}}_{mj}/\tau\right)}, \quad i = 1, 2, \ldots, n, \quad (5)$$

where τ is the softmax temperature, treated as a hyperparameter.

To ensure that TWiKers do not affect the model prior to training, we initialize the unconstrained kernels to a sharpened Central Dirac, such as $[0, 10, 0]$ for $n = 3$. This initialization enforces self-focus at the beginning, allowing the model to learn meaningful vicinity-aware modifications during training.

4 Experiments

In this section, we finetune GPT-2 (Radford et al., 2019) for causal language modeling using various English texts. The corpora, summarized in Table 1, span diverse genres including poetry, novels, drama, translations, and scientific articles. While TWiKers are broadly applicable to other languages and newer base models, we focus on English and GPT-2 due to resource constraints (see Limitations). Detailed data declarations are provided in Appendix A, and full engineering details can be found in Appendix B.

Specifically, the following setups are applied to ensure fair comparison across corpora:

1. **Data sampling**: The original corpora vary in length. From each corpus, we sample 2200 segments, each containing complete sentences and capped at 1000 tokens. The first 2000 segments are used for training, and the remaining 200 for evaluation.

2. **Two-stage finetuning**: We finetune GPT-2 on each corpus independently. We observe that some corpora (e.g., HarryPotter) converge much faster than others (e.g., Shakespeare) when trained directly with TWiKers. This discrepancy likely arises because different corpora start at varying distances from the pretrained model's local minimum–modern texts tend to be closer, while older or translated texts are farther away. To improve comparability across corpora, we adopt a two-stage training setup: each corpus is first finetuned for 30 epochs without TWiKers, allowing the model to adapt to the corpus. Then, we activate TWiKers and continue training for another 30 epochs.

3. **TWiKer hyperparameters**: TWiKers applied to keys or values can both shift attention toward neighboring tokens. To enhance semantic interpretability, we do not activate TWiKers for keys and values at the same time.

Corpus (Time Period) Data Source	**Linguistic Characteristics**
`Shakespeare` (1590–1616) Zahid (2021)	**Shakespeare's plays**: Contains 17 plays. Richly poetic language marked by inverted syntax, metaphor, and rhetorical patterning. Distinct from the straightforward diction of modern texts.
`Victorian` (1800–1900) Chapman (2022)	**British Poetry from the Victorian Era**: Contains 2216 transcribed poems. Favor formal adjectives, refined noun phrases, and measured syntax, contrasting with modern poetry's free, experimental style.
`NewPoems` (post 2000) Poetry Foundation (2023)	**Contemporary Poetry**: Contains 5000 sampled poems. Free verse with irregular syntax, simplified phrasing, and playful imagery. Many are written for children, with simple and creative language.
`War&Peace` (~1923) McKay (2016)	**English Translation of *War and Peace***: Formal adjectives and adverbs combine with expansive, subordinate clause-rich noun phrases. Retains traces of Russian syntactic structure, such as frequent use of passive voice and expressive, multi-clause constructions.
`RedChamber` (~1979) Internet Archive (2020)	**English Translation of *The Dream of the Red Chamber***: Employs nuanced adjectives and adverbs and balanced noun phrases to evoke a lyrical tone. Retains classical Chinese narrative style. In our clustering experiment, we include five versions translated by different authors.
`Dickens` (1836–1870) McAdams (2020)	**Novels by Charles Dickens**: Contains 15 selected books. Ornate prose with complex noun phrases, long compounds, and descriptive clauses. Language varies with character voice and social context.
`StKing` (1980–2000) Ajmain (2022)	**Novels by Stephen King**: Contains 20 selected books. Direct, vivid language with active verbs, informal phrasing, and narrative clarity. Blends colloquial realism with psychological tension.
`HarryPotter` (1997–2007) Kapoor (2024)	***Harry Potter***: Contains all seven books. Clear, child-friendly prose with simple sentence structures and vivid verbs. Language mixes fantasy world-building with British idiomatic expressions.
`Papers` (post 2000) Holbrook (2020)	**Scientific Articles**: Contains 1000 sampled paragraphs. Dense, impersonal prose with nominalization, passive constructions, and terminology. Emphasis on clarity, structure, and formal consistency.

Table 1: Corpora used for experiments, spanning diverse genres, time periods, and writing styles.

Unless stated otherwise (e.g., in ablation studies), we apply value convolution only, as it demonstrates greater robustness. The kernel size is fixed at three and shared across all attention heads. The softmax temperature is set to 0.4. Learning rates are fixed at 5×10^{-5} for model weights and 5×10^{-3} for `TWiKer` parameters, the latter compensating for small gradients near the Central Dirac initialization.

4.1 Lexical Attention Patterns

`TWiKers` offer direct insight into the local attention behavior of individual words. This subsection analyzes results from the `HarryPotter` corpus to demonstrate this.

We begin by examining the learned `TWiKer` weights without any processing. As shown in Figure 2, content words, such as `"Potter"` and `"gold"`, exhibit sharply peaked central weights, indicating that they bear attention primarily on themselves. In contrast, function words like `"the"` and `"and"` spread attention across neighboring positions, reflecting their syntactic role in structuring phrases rather than anchoring meaning. This difference aligns well with traditional linguistic distinctions between semantic and grammatical categories.

To quantify this behavior across broader lexical classes, we compute the average deviation of `TWiKer` weights from the Central Dirac for common parts of speech (PoS) tags. As shown in Figure 3, function words such as determiners and conjunctions exhibit greater deviations, while content-rich categories such as nouns and verbs remain closer to the central peak. This highlights the capacity of `TWiKers` to encode meaningful linguistic structure in an interpretable, unsupervised fashion.

Lexical handedness Another interesting property we observe is a directional asymmetry in the learned `TWiKer` weights. Among tokens whose central kernel weight is below 0.99, we categorize them as *left-handed* if the left value exceeds the right, and *right-handed* otherwise. In the `HarryPotter` corpus, we find that 9,570 tokens

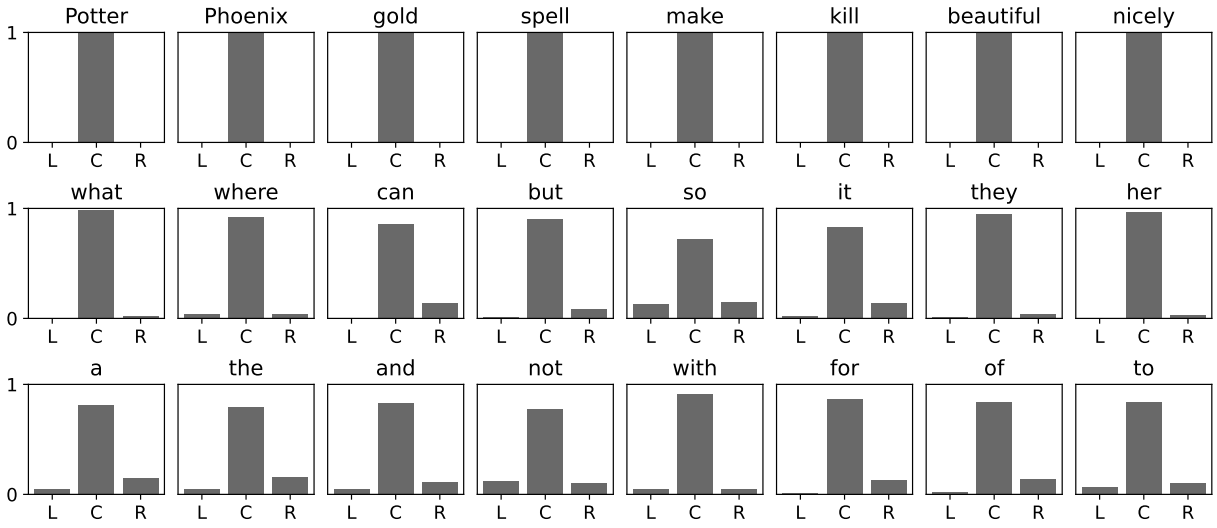


Figure 2: Learned TWiKer kernels for selected tokens in HarryPotter. Each triplet of bars shows the kernel weights for left (L), center (C), and right (R) positions. Content words show dominant center weights, while function words spread their attention to adjacent tokens.

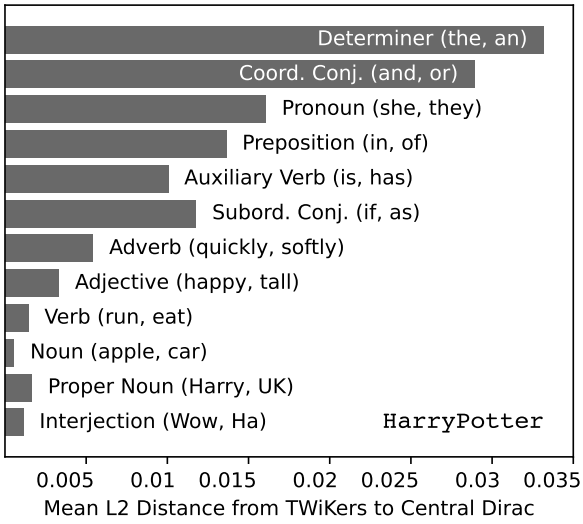


Figure 3: Mean deviation of learned TWiKers from Central Dirac $[0, 1, 0]$ across PoS tags in HarryPotter. Higher values indicate broader attention spread away from the token itself.

exhibit right-handedness, while only 84 are left-handed–a striking imbalance. This pattern aligns with the well-established fact that English is a right-branching language (Dryer, 1992; Du et al., 2020), where syntactic dependents such as complements and modifiers typically follow their heads. Function words (e.g., prepositions, subordinating conjunctions) often anticipate or introduce material to their right, naturally shifting attention forward in the sequence. This finding reinforces the idea that TWiKers internalize not only lexical category behavior but also broader structural tendencies inherent in natural language.

A key limitation in interpreting TWiKers arises from the use of subword tokenization in LLMs. To address this, we adopt two filtering measures. First, we exclude tokens that serve solely as suffixes–specifically, those not beginning with the "Ġ" (space) character. Second, for each token, we examine its PoS tags across the corpus and discard those that appear as affixes in more than 10% of their occurrences. This accounts for cases where a rare word begins with a common word, such as "upsurge" beginning with "up". We revisit this issue in more detail in Limitations.

4.2 Cross-Corpus Comparison

Figure 4 shows the overall TWiKer deviations from the Central Dirac across corpora. With deviations ranging from low to high, the corpora can be grouped into four categories: Academic, Poetic, Translations, and Novels. The results capture the strong influence of genre and stylistic conventions on attention patterns, with more structured or constrained texts yielding lower deviation, and freer, narrative-driven texts yielding higher deviation.

The Academic corpus (Papers) exhibits the lowest deviation, consistent with its rigid syntactic patterns and semantically dense constructions. Such writing minimizes contextual dependencies and maintains tight lexical focus.

The Poetic corpora follow, with their low deviation reflecting structured phrasing and rhythmic regularity. Notably, Victorian poetry shows lower

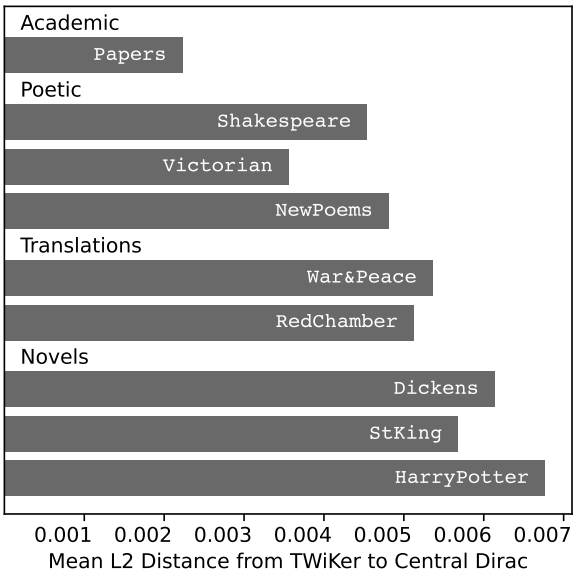


Figure 4: Mean deviation of learned `TWiKers` from the Central Dirac $[0, 1, 0]$ across nine corpora. Higher values suggest broader attention spread at the lexical level, often associated with more dynamic or loosely structured prose. Lower values indicate tighter, more self-contained word usage, reflecting semantically denser expression or a more formal tone.

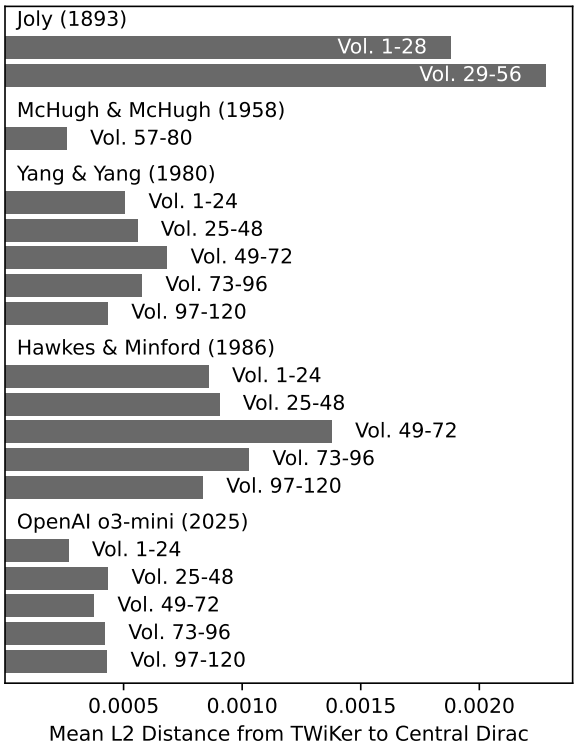


Figure 5: Mean deviation of learned `TWiKers` from Central Dirac $[0, 1, 0]$ across five English translations of *The Dream of the Red Chamber*.

deviation than `NewPoems`: the former adheres to metrical constraints and formal diction, while the latter–comprising free verse and children's poetry–permits flexible syntax and imaginative phrasing, increasing attention spread. `Shakespeare` occupies an intermediate position, reflecting its combination of poetic formality with syntactic inversion and dramatic rhythm.

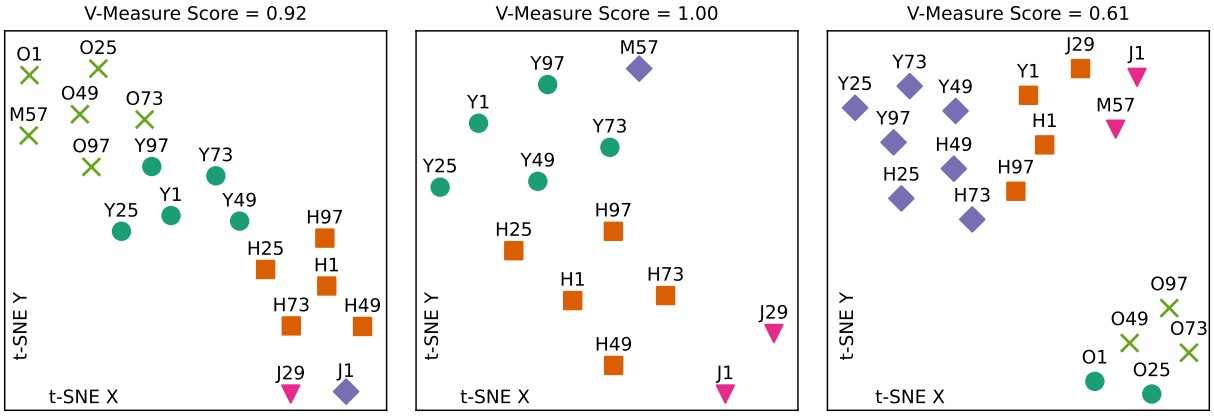
Novels, both translated and native, display the highest deviations, reflecting their narrative characteristic and syntactic variety. However, translated works (`War&Peace`, originally written in 19th-century Russian, and `RedChamber`, from 18th-century vernacular Chinese) exhibit somewhat lower deviation than native English novels, likely reflecting the relative syntactic compactness of their source languages and regularization introduced during translation. Within novels, `HarryPotter` exhibits the highest deviation, reflecting its conversational style, flexible sentence structures, and its blend of fantasy and colloquial language aimed at younger audiences.

To further investigate the relationship between genre, style, and attention spread, we examine `TWiKer` deviations by PoS tags in Appendix C, focusing on three corpora that diverge notably from general English norms.

4.3 Clustering Translations

As a real-world application, we use `TWiKers` to cluster different English translations of *The Dream of the Red Chamber* (红楼梦), one of the most celebrated novels in Chinese literature. A cloud over the novel's history is the uncertainty of its authorship. It is established that Cao Xueqin (曹雪芹) wrote the first 80 chapters, whereas the authorship of the final 40 chapters–possibly by Gao E (高鹗)–remains debated. While we are unable to resolve this historical mystery using GPT-2, it inspires us to analyze five full English translations of the novel through the lens of `TWiKers`.

We compare five English versions of Dream of the Red Chamber. The earliest, by H. Bencraft Joly (Joly, 1893), covers Chapters 1-56 in formal, archaic Victorian prose. It was later extended to Chapter 80 by Florence and Isabel McHugh (McHugh and McHugh, 1958), based not on the Chinese original but on Franz Kuhn's German version, adding an extra interpretive layer. The widely circulated edition by Yang Hsien-yi and Gladys Yang (Yang and Yang, 1980), published in China, is clear and faithful, prioritizing literal accuracy and accessibility over literary embellishment. David Hawkes' acclaimed transla-



(a) TWiKer-based, with AI translator (b) TWiKer-based, no AI translator (c) PoS-based, with AI translator

Figure 6: Clustering five English translations of *The Dream of the Red Chamber*. Each point represents one corpus (∼24 chapters), where the label shows the ground-truth (initial of the first translator's name and the starting chapter number; see Figure 5), and the marker shape indicates clustering results. We use a simple KMeans algorithm, starting from 100 different random states, and show the best results as above. Subfigures (a) and (b) are based on learned TWiKer weights, and (c), as a baseline, is based on PoS tag distributions.

tion (Hawkes and Minford, 1986) (Volumes I-III), completed by John Minford (Volumes IV-V), is widely accepted as the most literary version, with idiomatic prose and extensive cultural notes. Lastly, we include a machine-translated version by OpenAI's `o3-mini`, which is fluent and modern but may lack consistency in style between chapters.

We split the novel's 120 chapters into five segments, each containing ∼24 chapters, and use them as individual corpora to train TWiKer-enhanced GPT-2. Figure 5 shows the mean deviation of TWiKers from the Central Dirac. Even this single scalar metric can loosely differentiate translators.

For finer-grained analysis, we compute the average TWiKer deviation across PoS tags in each corpus, and apply KMeans clustering. Figure 6a shows the results using all five translations. Clustering is nearly perfect: the only notable misplacement is McHugh (M57) being absorbed into the AI cluster, while KMeans separates the two Joly corpora (J1, J29) to satisfy the five-cluster constraint. When we exclude the AI translation, Figure 6b shows that all corpora are clustered correctly. As a baseline, we also cluster based on simple PoS tag distributions (Figure 6c). While PoS can reflect some stylistic distinctions, its granularity is insufficient for accurate clustering, mainly due to mixing between the human-translated versions.

4.4 Ablation Study

To assess the impact of architectural choices on TWiKer behavior, we conduct an ablation study focused on three factors: kernel size, whether TWiKers are applied to keys or values, and whether they vary across attention heads. We observe that overall lexical patterns–such as content words being self-focused and function words distributing attention–remain consistent across the different configurations. Specifically, increasing the kernel size broadens attention spread; applying TWiKers to keys introduces strong variation in deviation for certain PoS tags; and head-specific TWiKers smooth deviation patterns and improve training convergence. These results, detailed in Appendix D, support that TWiKers serve as an effective inductive bias with small parameter footprint.

5 Conclusion

We have introduced TWiKers, a novel mechanism that equips transformers with token-specific convolutional kernels, providing a lightweight inductive bias toward vicinity reliance–an inherent property of human languages. Our experiments show that TWiKers capture meaningful lexical and syntactic behaviors without supervision: content words retain self-focus, while function words redistribute attention to neighboring tokens. This behavior generalizes across diverse corpora in English, reflecting both low-level linguistic regularities and high-level stylistic variation. By offering the first transformer weights with direct semantic interpretability, TWiKers may open new directions for linguistic analysis and the development of efficient, interpretable neural weights for language modeling.

Limitations

Our study has two main limitations. First, tokens do not always correspond to words under modern subword tokenization schemes. We address this by excluding suffix tokens from our analysis and consistently aligning tokens with complete words. While this filtering reduces the statistical power of our results, word-token alignment holds for the majority of the text-reflecting a key design principle of subword tokenizers. For more linguistically demanding applications, it is possible to pretrain models with larger, word-oriented vocabularies. Second, due to resource constraints, our experiments are conducted using GPT-2. Although an older model, GPT-2 retains the core architectural principles of causal decoder models, making it appropriate for testing our hypotheses. As a consequence, our analysis is limited to English. Extending `TWiKers` to languages with diverse morphological and syntactic structures remains an important direction for future work.

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A Data Declaration

We reviewed all nine corpora (see Table 1 for detailed descriptions of texts, time periods, and sources) to ensure that no personally identifying or offensive content was present. All materials are drawn from published literary works (public domain or widely distributed) and sampled scientific abstracts; we did not include private correspondence or unpublished personal data. Automated scripts scanned for full name patterns, email style strings, and offensive keywords; any hits were manually inspected and where necessary redacted. In the case of scientific articles, we also removed author bylines, institutional affiliations, and acknowledgments to protect anonymity.

All our data are in English. For originally non-English works (`War and Peace` and `The Dream of the Red Chamber`), we use their English translations; we also note multiple translator variants and demographic context (e.g. British vs. Russian vs. Chinese authors) in Table 1. For each corpus we record the number of works (e.g. 17 Shakespeare plays, 2 216 Victorian poems, 5 000 contemporary poems, 1 000 scientific article paragraphs, etc.), the source citation, and the predominant linguistic phenomena (e.g. inverted syntax and metaphor in Shakespeare, nominalization and passive constructions in scientific prose).

Across all corpora we processed approximately 1.2 million tokens. Each corpus was split at the document level into 80% train, and 20% test sets stratified by author and genre to preserve stylistic diversity. Detailed token counts per split (and per PoS tag) are provided in the supplementary Jupyter notebook, alongside document counts and PoS tag distributions.

B Engineering Details

We trained GPT-2 Base (117 M parameters) using a single NVIDIA V100 (40 GB) GPU. Total compute per corpus averaged under one GPU-hour (including both forward and backward passes), with all experiments running on the same V100 instance.

All main experiments reported in Section 4.1 used fixed hyperparameters: a learning rate of 5×10^{-5} for the Transformer weights and 5×10^{-3} for the `TWiKer` kernel parameters; a batch size of 6 for both training and evaluation; a `TWiKer` kernel size of 3 applied to the value projections in the attention mechanism; 2×30 training epochs; and a softmax temperature of 0.4 for normalizing `TWiKers`. Hyperparameter sweeps and ablation studies are discussed separately in Appendix D.

`TWiKers` are implemented through local modifications to Huggingface's `transformers` library. For data processing and analysis, we use SpaCy's `en_core_web_sm` model for part-of-speech tagging and NLTK's default rule-based tokenizer for sentence segmentation.

All results are reproducible via one-click experiment scripts and plotting utilities included in our released codebase and dataset package.

C TWiKers across PoS Tags in Corpora

In this Appendix, we present continued results for Section 4.2. Figure 7 shows the mean deviation of learned `TWiKers` from the Central Dirac kernel across nine corpora, broken down by PoS tags. These results reveal consistent trends in attention spread across lexical categories, while also highlighting stylistic variation among genres and time periods.

Charles Dickens and **Victorian Poetry** are the only corpora in which *prepositions* likely exhibit greater deviation than *determiners*. In Dickens, this may reflect a narrative style that tends to emphasize spatial density and rhythmic layering (Talukdar, 2024). For example, in *Great Expectations*:

> *"In a corner of the forge, the fire was burning brightly, and Joe was at his bellows, energetically puffing away."*

Here, *prepositions* such as "in", "of", and "at" likely function as structural anchors, distributing descriptive weight across the sentence. This style could be seen as aligning with Victorian literary aesthetics, where detailed spatial descriptions and atmospheric depth were common. `TWiKers` can

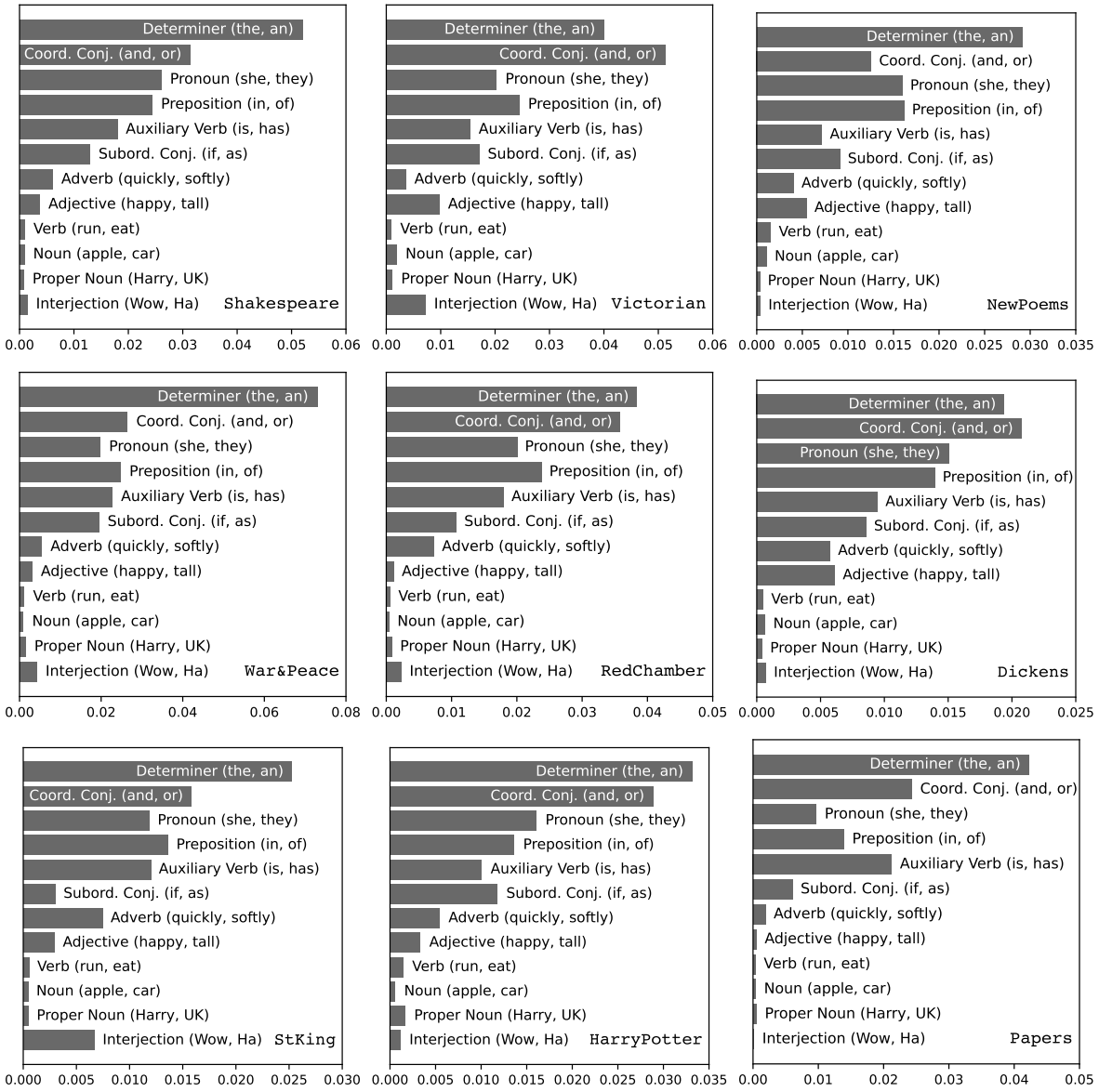

Figure 7: Mean deviation of learned `TWiKers` from Central Dirac $[0, 1, 0]$ across PoS tags in nine corpora.

learn to spread attention accordingly, capturing the rhetorical centrality of prepositional phrases in Dickens's prose.

Victorian poetry, though also showing elevated prepositional deviation, appears to follow a different stylistic rationale. Many literary scholars have noted that poets like Alfred Tennyson, Gerard Manley Hopkins, and Dante Gabriel Rossetti often favor determiner-noun imagery over clause-based narrative progression (Jewusiak, 2021; Blum, 1950; Drew, 1996). This stylistic choice likely reflects an emphasis on visual immediacy and symbolic precision, where *prepositions* often serve dual roles: indicating location and reinforcing prosodic balance. For instance, in Tennyson's *Tithonus*:

> *"The woods decay, the woods decay and fall..."*

Or Hopkins's *The Windhover*:

> *"The achieve of, the mastery of the thing!"*

Such usage suggests that *prepositions* and *determiners* function not merely as grammatical elements but as imagistic anchors. In contrast to narrative poets like Robert Browning, who rely heavily on *conjunctions* for logical progression ("And then she smiled..."), these poets emphasize stasis, vision, and repetition (Madhusudana, 2022). This static and visual emphasis connects closely with contemporary Victorian movements, such as the Pre-Raphaelite focus on symbolic and detailed vi-

sual imagery (Harrison, 2004; Hunt, 1968; Miras, 2024).

Additionally, **Victorian** poetry is the only corpus in which *determiners* likely deviate more than *conjunctions*. This could be attributed to the design of our dataset, which includes poets who often prioritize determiner-led imagery over logical connectives. For example, in Tennyson's *The Lady of Shalott*:

> *"The mirror crack'd from side to side;*
> *'The curse is come upon me,' cried*
> *The Lady of Shalott."*

Each instance of "the" may function as a visual or symbolic anchor–"mirror", "curse", "lady"–while *conjunctions* are comparatively minimized. This focus on determiner-led imagery is not universal among Victorian poets; for example, Browning and Christina Rossetti are known fo their reliance on clause-driven narrative progression. Our corpus likely foregrounds poets with a more determiner-centric style.

Stephen King presents a third, striking divergence: his is the only corpus where *interjections* appear to show the highest `TWiKer` deviation. This may be due to his focus on emotional immediacy, especially in horror and psychological suspense, where interjections often serve as narrative turning points (Takhtarova and Zubinova, 2018). From *The Green Mile*:

> *"We each owe a death, there are no exceptions, I know that, but sometimes, oh God, the Green Mile is so long."*

And in *Carrie*:

> *"No. Oh dear God, please no. (please let it be a happy ending)"*

These utterances do not carry strict syntactic function, but they likely help regulate pacing, convey fear, and anchor character perspective. `TWiKers` may capture this by assigning wider attention to such tokens, reflecting their dependence on surrounding discourse rather than immediate syntactic neighbors.

Taken together, these stylistically grounded deviations could support a key claim: `TWiKers` do not merely encode syntactic proximity–they can internalize genre conventions, authorial style, and literary tradition. The model's attention behavior highly resonates with deep patterns in English literary history, offering an interpretable bridge between data-driven learning and humanistic reading.

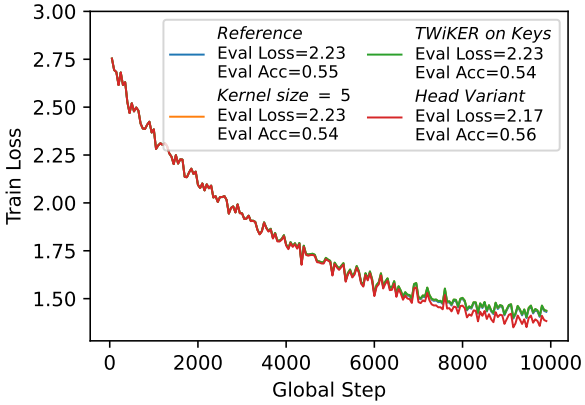

Figure 8: Training loss curves for ablation variants of `TWiKer` on the `HarryPotter` corpus. Final evaluation loss and accuracy are shown in the legend.

D Ablation Study

In this section, we examine how various architectural choices influence the behavior of `TWiKers`, using the `HarryPotter` corpus. The reference configuration uses a kernel size of 3, with `TWiKers` applied to the values in the attention mechanism, shared across all attention heads. This setup underpins the results presented in Section 4.1 and Section 4.2.

We consider three ablation variants, each modifying a single factor while keeping all others fixed:

- **Kernel size = 5**: Increases the `TWiKer` kernel width, allowing tokens to incorporate a broader local context.
- **TWiKer on Keys**: Applies `TWiKers` to the keys instead of the values, shifting the locality bias from the value aggregation to the query-side matching process.
- **Head Variant**: Assigns a separate `TWiKer` to each attention head within the input layer, enabling head-specific attention patterns.

Figure 8 shows the training loss curves under each configuration. As `TWiKers` introduce only a small number of additional parameters, they do not substantially affect optimization dynamics on their own. However, when allowed to vary by head (*Head Variant*), we observe slight improvements in both convergence rate and final evaluation accuracy. This suggests that `TWiKers` can serve as a lightweight and semantically grounded inductive bias in language modeling. Nevertheless, as noted in Limitations, all results are based on GPT-2. We do not claim general efficiency or scalability of

TWiKers at larger model scales, and leave this for future investigation.

Figure 9 shows the mean deviation of learned TWiKer kernels from the Central Dirac across PoS tags under different configurations. Across all these variants, the overall pattern holds: function words (e.g., determiners, conjunctions) tend to shift attention to neighbors, while content words (e.g., nouns, verbs) retain self-focus. Increasing the kernel size to five leads to broader deviation, especially for function words. Subordinate conjunctions show an outstanding relative increase in deviation when TWiKers are applied to keys, likely because their clause-linking function interacts more strongly with the query-side of attention. Allowing variation across heads (*Head Variant*) results in smoother distance distributions across PoS categories, suggesting a regularizing effect from distributing the locality pattern across multiple attention paths.

E Use of AI Assistants

We used ChatGPT-4o and DeepSeek R1 to help write Python code and improve sentences. No part of the code or paper was generated by AI without human guidance and verification.

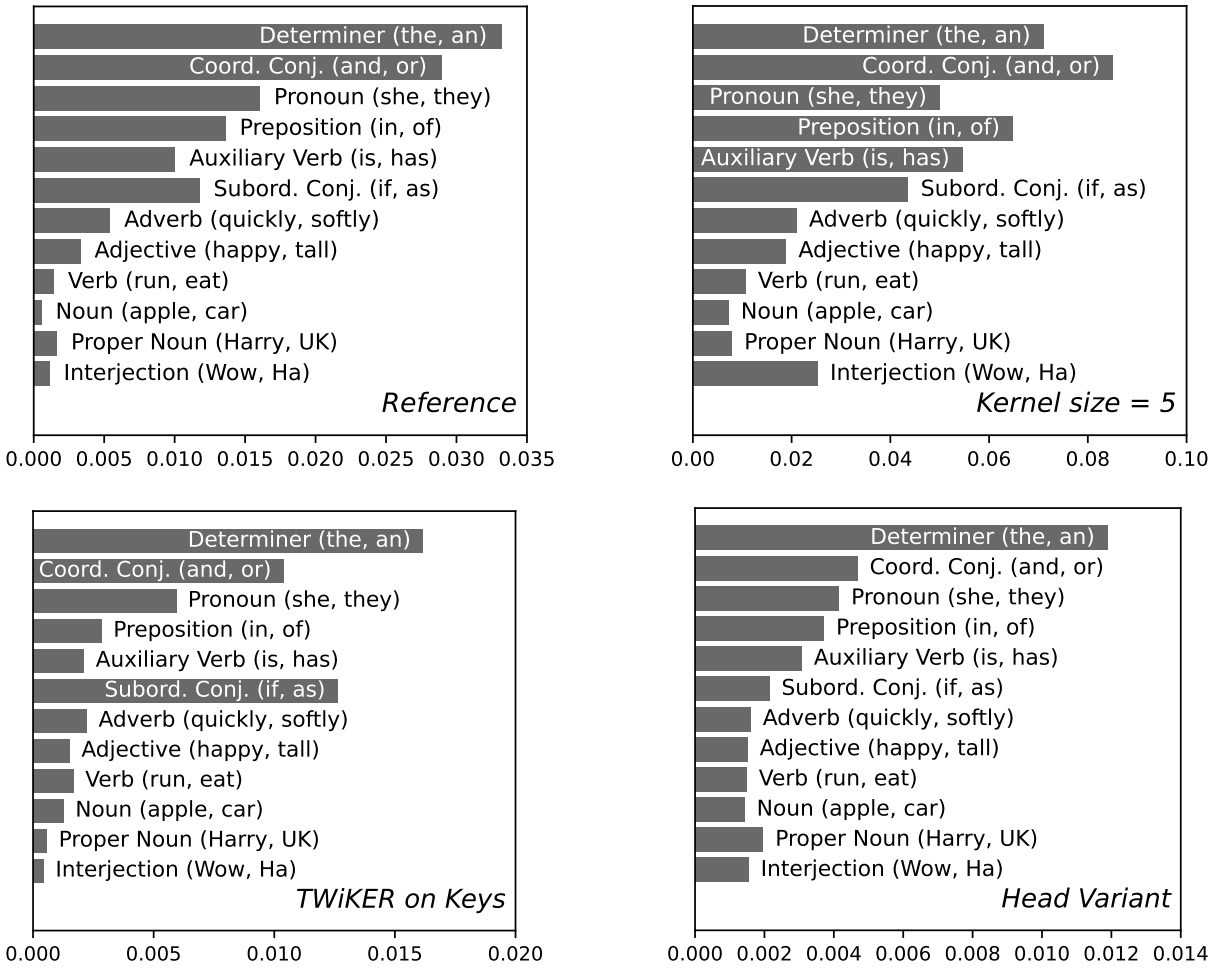

Figure 9: Mean deviation of learned `TWiKers` from the Central Dirac $[0, 1, 0]$ across PoS tags for different architectural configurations. *Reference*: kernel size = 3, `TWiKer` on values, head-invariant.