

829 Appendix

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857 A Datasheet for Datasets

858 The following section is answers to questions listed in datasheets for datasets.

859 A.1 Motivation

- 860 • Question: **For what purpose was the dataset created?** Was there a specific task in mind?
861 Was there a specific gap that needed to be filled? Please provide a description.

862 Answer: To evaluate the linguistic robustness of language models across diverse English
863 varieties by transforming Standard American English (SAE) datasets.

- 864 • Question: **Who created the dataset (e.g., which team, research group) and on behalf of**
865 **which entity (e.g., company, institution, organization)?**

866 Answer: The authors of this paper.

- 867 • Question: **Who funded the creation of the dataset?** If there is an associated grant, please
868 provide the name of the grantor and the grant name and number.

869 Answer: This work was supported by Institute for Information & communications Technol-
870 ogy Planning & Evaluation(IITP) grant funded by the Korea government(MSIT) (RS-2019-
871 II190075, Artificial Intelligence Graduate School Program(KAIST)).

872 A.2 Composition

- 873 • Question: **What do the instances that comprise the dataset represent (e.g., documents,**
874 **photos, people, countries)?** Are there multiple types of instances (e.g., movies, users,
875 and ratings; people and interactions between them; nodes and edges)? Please provide a
876 description.

877 Answer: QA datasets (sentences) transformed into various English varieties.

- 878 • Question: **How many instances are there in total (of each type, if appropriate)?**

879 Answer: There are about 952K instances in total.

- 880 • Question: **Does the dataset contain all possible instances or is it a sample (not necessarily**
881 **random) of instances from a larger set?** If the dataset is a sample, then what is the larger
882 set? Is the sample representative of the larger set (e.g., geographic coverage)? If so, please
883 describe how this representativeness was validated/verified. If it is not representative of the
884 larger set, please describe why not (e.g., to cover a more diverse range of instances, because
885 instances were withheld or unavailable).

886 Answer: The dataset contains all instances from the existing benchmark datasets.

- 887 • Question: **What data does each instance consist of?** “Raw” data (e.g., unprocessed text or
888 images) or features? In either case, please provide a description.

889 Answer: Each instance consists of the transformed text, answer choices, and label.

- 890 • Question: **Is there a label or target associated with each instance?** If so, please provide a
891 description.

892 Answer: Yes, each label comes from the original QA datasets.

- 893 • Question: **Is any information missing from individual instances?** If so, please provide a
894 description, explaining why this information is missing (e.g., because it was unavailable).
895 This does not include intentionally removed information, but might include, e.g., redacted
896 text.

897 Answer: No, there is no information missing from individual instances.

- 898 • Question: **Are relationships between individual instances made explicit (e.g., users’**
899 **movie ratings, social network links)?** If so, please describe how these relationships are
900 made explicit.

901 Answer: No.

- 902 • Question: **Are there recommended data splits (e.g., training, development/validation,**
903 **testing)?** If so, please provide a description of these splits, explaining the rationale behind
904 them.

905 Answer: This dataset is for testing only.

906 • Question: **Are there any errors, sources of noise, or redundancies in the dataset?** If so,
 907 please provide a description.

908 Answer: No, we have verified that there are no errors in the datasets.

909 • Question: **Is the dataset self-contained, or does it link to or otherwise rely on external**
 910 **resources (e.g., websites, tweets, other datasets)?** If it links to or relies on external
 911 resources, a) are there guarantees that they will exist, and remain constant, over time; b) are
 912 there official archival versions of the complete dataset (i.e., including the external resources
 913 as they existed at the time the dataset was created); c) are there any restrictions (e.g., licenses,
 914 fees) associated with any of the external resources that might apply to a dataset consumer?
 915 Please provide descriptions of all external resources and any restrictions associated with
 916 them, as well as links or other access points, as appropriate.

917 Answer: Our dataset is self-contained.

918 • Question: **Does the dataset contain data that might be considered confidential (e.g.,**
 919 **data that is protected by legal privilege or by doctor–patient confidentiality, data that**
 920 **includes the content of individuals’ non-public communications)?** If so, please provide a
 921 description.

922 Answer: No.

923 • Question: **Does the dataset contain data that, if viewed directly, might be offensive,**
 924 **insulting, threatening, or might otherwise cause anxiety?** If so, please describe why.

925 Answer: No.

926 A.3 Preprocessing/cleaning/labeling

927 • Question: **Was any preprocessing/cleaning/labeling of the data done (e.g., discretization**
 928 **or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of**
 929 **instances, processing of missing values)?** If so, please provide a description. If not, you
 930 may skip the remaining questions in this section.

931 Answer:

932 • Question: **Was the “raw” data saved in addition to the preprocessed/cleaned/labeled**
 933 **data (e.g., to support unanticipated future uses)?** If so, please provide a link or other
 934 access point to the “raw” data.

935 Answer: No.

936 • Question: **Is the software that was used to preprocess/clean/label the data available?** If
 937 so, please provide a link or other access point.

938 Answer:

939 – Google Sheets: <https://docs.google.com/spreadsheets/>

940 – Python: <https://www.python.org/>

941 A.4 Uses

942 • Question: **Has the dataset been used for any tasks already?** If so, please provide a
 943 description.

944 Answer: No.

945 • Question: **Is there a repository that links to any or all papers or systems that use the**
 946 **dataset?** If so, please provide a link or other access point.

947 Answer: No.

948 • Question: **What (other) tasks could the dataset be used for?**

949 Answer: N/A

950 • Question: **Is there anything about the composition of the dataset or the way it was**
 951 **collected and preprocessed/cleaned/labeled that might impact future uses?** For example,
 952 is there anything that a dataset consumer might need to know to avoid uses that could result

953 in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or
954 other risks or harms (e.g., legal risks, financial harms)? If so, please provide a description. Is
955 there anything a dataset consumer could do to mitigate these risks or harms?

956 Answer: N/A

957 • Question: **Are there tasks for which the dataset should not be used?** If so, please provide
958 a description.

959 Answer: N/A

960 A.5 Distribution

961 • Question: **Will the dataset be distributed to third parties outside of the entity (e.g.,**
962 **company, institution, organization) on behalf of which the dataset was created?** If so,
963 please provide a description.

964 Answer: Yes, the dataset will be made publicly accessible through Hugging Face.

965 • Question: **How will the dataset will be distributed (e.g., tarball on website, API,**
966 **GitHub)?** Does the dataset have a digital object identifier (DOI)?

967 Answer: The datasets will be distributed on Hugging Face with public access.

968 • Question: **When will the dataset be distributed?**

969 Answer: The dataset is publicly available on Hugging Face since May 12, 2025.

970 • Question: **Will the dataset be distributed under a copyright or other intellectual prop-**
971 **erty (IP) license, and/or under applicable terms of use (ToU)?** If so, please describe this
972 license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any
973 relevant licensing terms or ToU, as well as any fees associated with these restrictions.

974 Answer: The datasets are distributed under the CC BY-SA 4.0 license.

975 • Question: **Have any third parties imposed IP-based or other restrictions on the data**
976 **associated with the instances?** If so, please describe these restrictions, and provide a link
977 or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any
978 fees associated with these restrictions.

979 Answer: No.

980 • Question: **Do any export controls or other regulatory restrictions apply to the dataset**
981 **or to individual instances?** If so, please describe these restrictions, and provide a link or
982 other access point to, or otherwise reproduce, any supporting documentation.

983 Answer: No.

984 A.6 Maintenance

985 • Question: **Who will be supporting/hosting/maintaining the dataset?**

986 Answer: The dataset is hosted on Hugging Face.

987 • Question: **How can the owner/curator/manager of the dataset be contacted (e.g., email**
988 **address)?**

989 Answer: Contact the authors of this paper via email.

990 • Question: **Is there an erratum?** If so, please provide a link or other access point.

991 Answer: No.

992 • Question: **Will the dataset be updated (e.g., to correct labeling errors, add new instances,**
993 **delete instances)?** If so, please describe how often, by whom, and how updates will be
994 communicated to dataset consumers (e.g., mailing list, GitHub)?

995 Answer: The datasets will be updated if necessary.

996 • Question: **If the dataset relates to people, are there applicable limits on the retention of**
997 **the data associated with the instances (e.g., were the individuals in question told that**
998 **their data would be retained for a fixed period of time and then deleted)?** If so, please
999 describe these limits and explain how they will be enforced.

1000 Answer: The dataset does not relate with people.

- 1001 • Question: **Will older versions of the dataset continue to be supported/hosted/main-**
 1002 **tained?** If so, please describe how. If not, please describe how its obsolescence will be
 1003 communicated to dataset consumers.
- 1004 Answer: Yes.
- 1005 • Question: **If others want to extend/augment/build on/contribute to the dataset, is there a**
 1006 **mechanism for them to do so?** If so, please provide a description. Will these contributions
 1007 be validated/verified? If so, please describe how. If not, why not? Is there a process for
 1008 communicating/distributing these contributions to dataset consumers? If so, please provide
 1009 a description.
- 1010 Answer: No, our datasets are freely available for others to use.

1011 **B Experiment Setting**

1012 **B.1 Computer Resources**

1013 Experiments were conducted using four NVIDIA RTX A6000 GPUs and two NVIDIA A100-SXM4-
 1014 80GB GPUs. Our implementation is built on vLLM (v0.5.5), PyTorch (v2.4.0), Hugging Face
 1015 Transformers (v4.47.0), and Datasets (v3.1.0). On average, each dataset required approximately 10
 1016 hours for transformation.

1017 **C Dataset Construction**

1018 **C.1 English Dialects**

1019 **C.1.1 Electronic World Atlas of Varieties of English (eWAVE)**

1020 The Electronic World Atlas of Varieties of English (eWAVE) [34] is a curated database document-
 1021 ing 235 linguistic features across 77 English varieties. Developed by 84 professional linguists and
 1022 grounded in 175 peer-reviewed sources, eWAVE provides a structured taxonomy of features spanning
 1023 12 grammatical categories: Pronouns, Noun Phrase, Tense and Aspect, Modal Verbs, Verb Morphol-
 1024 ogy, Negation, Agreement, Relativization, Complementation, Adverbial Subordination, Adverbs and
 1025 Prepositions, and Discourse and Word Order. Each feature is accompanied by illustrative examples.
 1026 Varieties are annotated with six levels of feature prevalence: (i) feature is pervasive or obligatory, (ii)
 1027 feature is neither pervasive nor extremely rare, (iii) feature exists, but is extremely rare, (iv) attested
 1028 absence of feature, (v) feature is not applicable (given the structural make-up of the variety/P/C), and
 1029 (vi) no information on feature is available.

1030 **C.1.2 Dialect Selection**

1031 We first mapped the presence strength of each feature per dialect to one of four discrete levels.

- 1032 • feature is pervasive or obligatory: 1.0
- 1033 • feature is neither pervasive nor extremely rare: 0.5
- 1034 • feature exists, but is extremely rare: 0.25
- 1035 • attested absence of feature, feature is not applicable, no information on feature is available: 0

1036 We then applied Singular Value Decomposition (SVD) for dimensionality reduction, retaining 90%
 1037 of the variance. Using the reduced feature representations for each dialect, we performed K-Nearest
 1038 Neighbors (KNN) clustering with the number of clusters set to 5. The choice of 5 clusters was
 1039 informed by both the Elbow Method and Silhouette Scores, which indicated that 5 was the most
 1040 optimal number of clusters. Then we selected clusters with famous English dialects such as African
 1041 American Vernacular English and Welsh English. The final 18 dialects and their abbreviations are
 1042 as follows: African American Vernacular English (AAVE), Irish English (IrE), Australian English
 1043 (AuE), Bahamian English (BahE), East Anglian English (EAngE), Appalachian English (AppE),
 1044 English dialects in the Southeast of England (SE-Eng), Australian Vernacular English (AuE-V),
 1045 English dialects in the North of England (NE-Eng), English dialects in the Southwest of England
 1046 (SW-Eng), Manx English (Manx), New Zealand English (NZE), Newfoundland English (NfE), Ozark

English (OzE), Scottish English (ScE), Southeast American enclave dialects (SE-AmE), Tristan da Cunha English (TdCE), Welsh English (WaE).

C.2 ESL English-L1

C.2.1 Number of Samples in Compiled Dataset.

Table 6 shows the number of samples per L1 and per CEFR level collected from three learner corpora: CLC-FCE [68], ICLE [22], and EFCamDat [18].

Table 6: Number of samples collected from CLC-FCE, ICLE, and EFCamDat.

	CLC-FCE		ICLE		EFCamDat		Total	
	A	B	A	B	A	B	A	B
Arabic	0	0	0	0	24,155	4,857	24,155	4,857
Chinese-Mandarin	9	107	1	45	106,654	22,289	106,664	22,441
French	2	245	0	0	22,244	9,646	22,246	9,891
German	2	120	3	42	25,040	14,501	25,045	14,663
Italian	2	121	1	8	22,787	11,672	22,790	11,801
Japanese	6	134	10	171	11,653	5,081	11,669	5,386
Portuguese	1	114	1	43	248,200	61,751	248,202	61,908
Russian	10	134	0	12	35,081	13,287	35,091	13,433
Spanish	16	351	6	47	52,786	11,456	52,808	11,854
Turkish	8	126	0	61	7,899	2,237	7,907	2,424

C.2.2 CEFR Pseudo-Label Generation

The CLC-FCE and ICLE datasets do not include annotated CEFR levels. To address this, we employed gpt-4o-mini-2024-07-18 to generate pseudo-CEFR labels. The prompt used for label generation is provided in Table 7.

Table 7: Prompt used for pseudo CEFR label generation.

System:
You are a linguistic expert.
User:
Classify the given sentence among three CEFR levels (A, B, C). Respond only CEFR level.
Sentence: {sentence}

C.2.3 Outputs from the Automatic Grammar Checker

The outputs from the automatic grammar checker are overly specific, identifying narrow error types such as “I told her (to) break a leg” or “this render (renders) the ...”. To enable more effective analysis, we consolidated similar low-level errors into broader categories. For instance, the category “Omission of a Preposition” includes examples like “I told her (to) break a leg” and “It would be great (to) write a story.” The category “Mismatch between Article and Noun” captures cases such as “I like to use a pens and paper,” “I have received a 150 likes,” and “The cat is an animals.”

In total, we define 42 higher-level categories: “Confusion between effects and affects”, “Double negation”, “Gerund complement after psych/perception verb”, “Inappropriate formulaic closing”, “Incorrect existential agreement with plural noun”, “Incorrect passive voice usage”, “Incorrect pluralization after ‘either of’”, “Incorrect use of ‘if’ instead of ‘whether’”, “Incorrect use of gerund after ‘advise’”, “Incorrect verb usage with auxiliary”, “Mismatch between article and noun”, “Mismatch between noun and adjective”, “Mismatch between subject and verb”, “Missing complementizer ‘to’ after ‘allow’”, “Missing determiner after quantifier”, “Misusage of irregular past tense verbs”, “Misuse of ‘have’ and ‘having’”, “Non-standard negation with ‘let’s’”, “Omission of a preposition”, “Omission of a verb”, “Omission of object pronoun”, “Omission of required articles”, “Omission

1073 of subject”, “Plural noun required after quantifier phrase”, “Redundant discourse marker usage”,
 1074 “Redundant modal construction”, “Redundant phrase repetition”, “Redundant verb in question form”,
 1075 “Singular form in fixed polite expression”, “Usage of ‘couple times’ instead of ‘a couple of times’ ”,
 1076 “Usage of a plural noun when a singular form is required”, “Usage of a plural noun where a singular
 1077 is required after ‘is there any’ ”, “Usage of a singular noun when a plural form is required”, “Usage
 1078 of an adjective where an adverb is required”, “Usage of an auxiliary verb when unnecessary”, “Usage
 1079 of an incorrect past participle form”, “Usage of first-person subject with ‘according to’ ”, “Usage of
 1080 passive voice when active voice is required’ ”, “Usage of plural auxiliary ‘do’ with singular subject
 1081 ‘anyone’ ”, “Use of ‘much’ with countable noun”, “Use of continuous aspect with stative verbs”,
 1082 “Use of plural noun with each/every.”

1083 C.2.4 L1-Specific Features

1084 The following are the extracted features categorized by L1.

- 1085 • Arabic: Usage of a plural noun where a singular is required after ‘is there any’, Incorrect passive
 1086 voice usage, Usage of ‘couple times’ instead of ‘a couple of times’, Omission of a preposition,
 1087 Mismatch between article and noun, Omission of a verb, Usage of a singular noun when a plural
 1088 form is required, Omission of subject, Missing determiner after quantifier, Mismatch between
 1089 article and noun
- 1090 • Chinese-Mandarin: Usage of plural auxiliary ‘do’ with singular subject ‘anyone’, Inappropriate
 1091 formulaic closing, Mismatch between subject and verb, Singular form in fixed polite expression,
 1092 Omission of subject, Usage of an incorrect past participle form, Mismatch between article and
 1093 noun, Incorrect existential agreement with plural noun, Usage of passive voice when active voice
 1094 is required
- 1095 • French: Non-standard negation with ‘let’s’, Usage of ‘couple times’ instead of ‘a couple of times’,
 1096 Redundant verb in question form, Misuse of ‘have’ and ‘having’, Usage of a plural noun where a
 1097 singular is required after ‘is there any’, Use of plural noun with each/every, Gerund complement
 1098 after psych/perception verb, Omission of a preposition, Omission of a verb, Usage of first-person
 1099 subject with ‘according to’
- 1100 • German: Incorrect passive voice usage, Usage of ‘couple times’ instead of ‘a couple of times’,
 1101 Misuse of ‘have’ and ‘having’, Gerund complement after psych/perception verb, Omission of a
 1102 preposition, Incorrect verb usage with auxiliary, Misusage of irregular past tense verbs, Use of
 1103 ‘much’ with countable noun, Usage of an adjective where an adverb is required, Incorrect use of
 1104 gerund after ‘advise’
- 1105 • Italian: Incorrect use of ‘if’ instead of ‘whether’, Usage of ‘couple times’ instead of ‘a couple of
 1106 times’, Usage of a plural noun where a singular is required after ‘is there any’, Redundant discourse
 1107 marker usage, Incorrect pluralization after ‘either of’, Gerund complement after psych/perception
 1108 verb, Use of plural noun with each/every, Usage of a singular noun when a plural form is required,
 1109 Omission of a verb, Misusage between ‘not’ and ‘never’
- 1110 • Japanese: Use of continuous aspect with stative verbs, Mismatch between noun and adjective, Re-
 1111 dundant modal construction, Usage of a singular noun when a plural form is required, Omission of
 1112 a preposition, Gerund complement after psych/perception verb, Missing determiner after quantifier,
 1113 Plural noun required after quantifier phrase, Omission of required articles, Omission of object
 1114 pronoun
- 1115 • Portuguese: Omission of a preposition, Omission of subject, Gerund complement after psych/per-
 1116 ception verb, Usage of an auxiliary verb when unnecessary, Usage of a singular noun when a
 1117 plural form is required, Missing complementizer ‘to’ after ‘allow’, Singular form in fixed polite
 1118 expression, Redundant phrase repetition, Double negation, Incorrect existential agreement with
 1119 plural noun
- 1120 • Russian: Redundant verb in question form, Mismatch between article and noun, Misusage of
 1121 preposition, Mismatch between subject and verb, Omission of a verb, Omission of subject, Miss-
 1122 ing complementizer ‘to’ after ‘allow’, Omission of a preposition, Redundant verb, Redundant
 1123 preposition
- 1124 • Spanish: Non-standard negation with ‘let’s’, Incorrect pluralization after ‘either of’, Mismatch
 1125 between article and noun, Omission of subject, Omission of a preposition, Incorrect verb usage

Table 8: Prompt for generating transformation guidelines

System:

You are a linguistic expert. I am a student trying to understand the given linguistic feature and transform a sentence reflecting the feature. As an expert, first explain the linguistic characteristics of the given linguistic feature. Then, outline detailed steps to transform a given sentence to reflect the characteristic, breaking the process into two main phases: Qualification and Application. Qualification refers to steps that identify if the linguistic feature is applicable to the given sentence in yes/no question format where answers to all questions should be 'yes' if feature dialect is applicable. Here, questions in qualification should be strictly related to lexical rules and should not ask for any decisions asking for significance or emotions. The questions should also not include questions about context, culture, or metaphors. Application refers to the action items that a model should take in order to reflect the given linguistic feature. All questions and action items should strictly be related to lexicon. All questions and action items should not include context, culture, or metaphor where answers might differ by people such as determining significant role or emotional attachment.

User:

Linguistic Feature: She/her used for inanimate referents.

Description: Pronouns, pronoun exchange, nominal gender.

Examples: The boat I had, was a seventy-two foot boat., She was built in Joneses-Slip in nineteen-fifty-five by my father., She's a nice bike., I left the boat there as she was., This is another pot and saucer., A bit dusty! You see that one isn't exactly glazed proper, burnt proper is she?, She's a twenty point five metre sloop again designed by Kel Steinman an Australian, So the Bransfield is the BAS ship then? Yeah she was the sort of kingpin until they brought the James Clark Ross

Assistant:

Linguistic Characteristic: She/Her Used for Inanimate Referents

The phenomenon of using 'she' or 'her' for inanimate objects is primarily influenced by cultural associations, personification, or grammatical gender in certain languages. In English, it is less common but can occur in specific contexts, such as referring to ships, cars, or countries, often reflecting affection, personification, or historical conventions. This use can evoke an emotional connection or imply a particular viewpoint about the inanimate referent.

Steps to Transform a Sentence: To transform a given sentence to reflect the use of 'she/her' for inanimate referents, we can break the process down into two main phases: Qualification and Application.

Qualification

1. Is there an inanimate referent in the sentence?
2. Does the original sentence contain a pronoun that can be replaced with 'she' or 'her'?

If the answers to all relevant questions are "Yes," then the linguistic feature is applicable.

Application

1. Identify the inanimate referent in the sentence that will be modified.
2. Replace any pronouns referring to the inanimate referent with "she" or "her."

User:

Linguistic Feature: {linguistic feature}

Description: {description of linguistic feature}

Examples: {examples of linguistic feature}

- 1126 with auxiliary, Usage of a singular noun when a plural form is required, Missing Determiner after
 1127 Quantifier, Redundant verb, Misusage of article in uncountable noun
- 1128 • Turkish: Confusion between effects and affects, Usage of first-person subject with 'according
 1129 to', Usage of a singular noun when a plural form is required, Omission of a preposition, Missing
 1130 complementizer 'to' after 'allow', Omission of subject, Usage of a plural noun when a singular form
 1131 is required, Missing determiner after quantifier, Mismatch between article and noun, Redundant
 1132 adverb

Table 9: Examples of transformation guidelines.

Feature: Myself/meself instead of I in coordinate subjects

Qualification:

1. Is there a coordinate subject in the sentence? A coordinate subject is formed when two subjects are joined by a conjunction like ‘and’ or ‘or’.
2. Does the coordinate subject include ‘I’?

If the answers to all relevant questions are ‘Yes’, then the linguistic feature is applicable.

Application:

1. Identify the coordinate subject in the sentence that includes ‘I’.
 2. Replace ‘I’ with ‘myself’ in the coordinate subject.
-

Feature: Omission of Required Articles

Qualification:

1. Does the sentence contain a noun that requires an article (‘a’, ‘an’, or ‘the’) for grammatical correctness or clarity?
2. Is the noun countable and in singular form, or does it refer to something specific that needs ‘the’?

If the answers to all relevant questions are ‘Yes’, then the linguistic feature is applicable.

Application:

1. Identify the noun(s) that require an article for grammatical correctness.
 2. Remove the article (‘a’, ‘an’, or ‘the’) preceding the noun or leave the noun without any article.
-

1133 C.3 Transformation Guideline Generation

1134 We use gpt-4-0613 to generate transformation guidelines via one-shot prompting, with a temperature
 1135 of 0.8 and top-*p* sampling set to 0.95. The model is provided with the name of the linguistic feature,
 1136 a brief description, and representative examples. It is then instructed to (1) describe the linguistic
 1137 characteristics of the feature, and (2) outline a step-by-step transformation procedure consisting
 1138 of two phases: *Qualification*, which checks whether the feature applies to a given sentence, and
 1139 *Application*, which modifies the sentence accordingly.

1140 We emphasize that the transformation process should focus strictly on lexical rules, avoiding subjective
 1141 elements such as emotional or cultural interpretation, metaphor, or judgments of significance. The
 1142 full prompt used for generating transformation guidelines is shown in Table 8, and examples of the
 1143 resulting guidelines are presented in Table 9.

1144 C.4 Transforming into English Varieties

1145 C.4.1 Transformation of Vocabulary into Target CEFR Levels

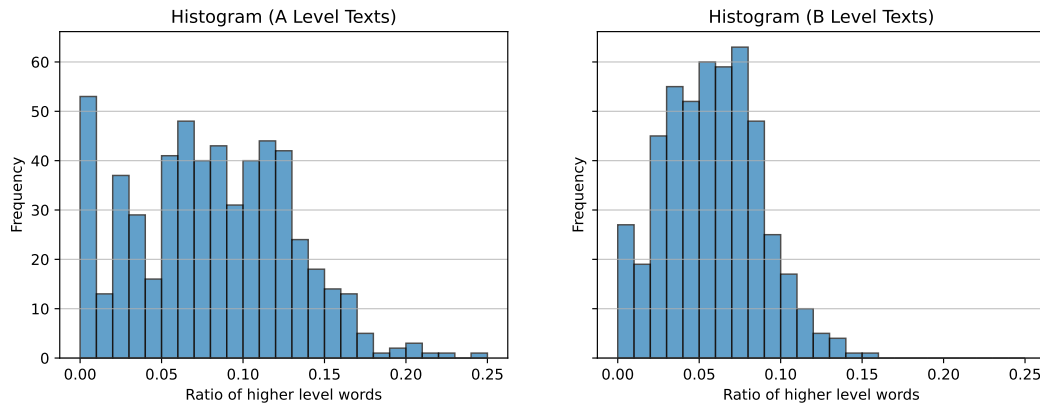


Figure 3: Histograms of distributions of higher-level word usage in CEFR A and CEFR B texts.

1146 To ensure that the transformed outputs for ESL English varieties reflect realistic proficiency levels,
 1147 we incorporated a vocabulary substitution step guided by CEFR-level annotations. To acknowledge
 1148 that ESL learners often know a small fraction of advanced words even at lower proficiency levels, we
 1149 first analyze a CEFR-labeled English text dataset to find out the ratio of higher-level words used by
 1150 lower CEFR proficiency level learners, as mentioned in Section 3.3. Figure 3 presents the distribution
 1151 of higher-level vocabulary in the dataset (*e.g.*, B or C level words in A level texts). Notably, for both
 1152 target levels A and B, at least 90% of the samples contain no more than 15% of vocabulary from
 1153 higher CEFR levels than the designated target level. This empirical finding motivated our decision to
 1154 allow up to 15% of higher-level vocabulary in transformed outputs. This threshold balances fidelity
 1155 to learner-level constraints with linguistic realism, acknowledging that ESL learners often know a
 1156 small fraction of advanced words even at lower proficiency levels.

Table 10: Vocabulary pseudo-label prompt.

System: You are an expert in classifying vocabulary into CEFR levels. Given a single word, classify it into its appropriate CEFR level when used with its most common definition. If it is a proper noun, answer with A1. Answer only with one of the following: A1, A2, B1, B2, C1, C2.
User: {word}

Table 11: Vocabulary transformation prompt.

System: You are an expert in transforming vocabulary of higher CEFR levels to level {target_level}. You are given higher level words that appear in the question: {words_to_transform}. Please replace at least {min_transform_words} words with synonyms in level {target_level}.
User: {question_text}

1157 Table 10 shows the prompt used for finding pseudo-labels for words without a CEFR label in
 1158 the Oxford vocabulary lists, and Table 11 presents the prompt used for transforming higher-level
 1159 vocabulary in a sentence to a target level. The value of min_transform_words is set to 15% of the
 1160 total word count in question_text and serves as the threshold for permitted higher-level words.
 1161 Table 12 presents the transformation success rates by CEFR level and dataset, showing how often our
 1162 pipeline was able to produce outputs that met CEFR-level vocabulary constraints while preserving
 1163 semantic equivalence.

Table 12: Number and ratio of valid vocabulary transformations by dataset.

Dataset	Size	Target CEFR	Valid Transf.	Transf. Ratio
MMLU	14042	A	7246	51.6%
		B	11970	85.2%
GSM8K	1319	A	1219	92.4%
		B	1315	99.7%
ARC	1172	A	774	66.0%
		B	1132	96.6%
HellaSwag	10042	A	7593	75.6%
		B	9903	98.6%
TruthfulQA	817	A	623	76.3%
		B	781	95.6%
WinoGrande	1267	A	945	74.6%
		B	1247	98.4%

1164 C.5 Prompts used for Transformation

1165 Table 13 presents the one-shot prompt used to transform a Standard American English (SAE) sentence
 1166 s into a target variety using the feature transformation model T . Each transformation is guided by

Table 13: Prompt for transforming into varieties.

System: Your task is to rephrase the given sentence by following the guideline. {transformation guideline} 1. **Qualification**: - Answer the qualification questions for the linguistic feature with either "yes" or "no." - Answer the questions in a very strict manner. - Proceed to the next step only if **all** answers are "yes." - Otherwise, stop in qualification phase with generating **Transformed Sentence:** (No change)'. 2. **Application**: - Make only the **necessary changes** to apply the linguistic feature, ensuring no loss of information. - Provide the final transformed sentence, adhering strictly to the format and structure of the given example. ### Mandatory - Proceed to Application only if all answers to the qualification questions are 'yes'. - Preserve the structure of the original sentence as much as possible with no information loss. - Follow the guideline, not considering standard English grammar. - Final sentence should start with **Transformed Sentence:** either with sentence of (No change). User: **Original Sentence**: {example sentence} Assistant: {example output} User: **Original Sentence**: {SAE written sentence}
--

Table 14: Prompt for semantic check.

User: Determine whether the meaning of Sentence 1 is significantly altered or lost in Sentence 2. ### Consideration - All keywords from Sentence 1 should be in Sentence 2. - All numbers in Sentence 1 should match with Sentence 2. - Focus on core information only. - Ignore grammar; it is not a factor for consideration. - Missing or incorrect prepositions should not be considered. - Ignore repetition of phrases. Repetition is not a factor for consideration. - Base your decision solely on whether essential information is missing. Respond with either 'yes' or 'no' only. Sentence 1: {SAE written sentence} Sentence 2: {transformed sentence} Answer:

1167 a feature-specific guideline and example. The model is instructed to follow the guideline strictly,
 1168 preserving the structure and core meaning of the original sentence while disregarding grammatical
 1169 correctness.

1170 To ensure semantic fidelity, we employ a semantic checker model S using a zero-shot prompt, as
 1171 shown in Table 14. The verification process emphasizes the preservation of key content elements
 1172 such as keywords, numerical information, and core propositions, while ignoring minor grammatical
 1173 deviations, including incorrect or missing prepositions and redundancy.

Table 15: Average number of features applied per sample and proportion of transformed samples in dialect.

	MMLU	ARC	TruthfulQA	GSM8K	Hellaswag	WinoGrande
AAVE	1.12 / 61.8%	1.17 / 65.1%	0.76 / 45.0%	0.80 / 54.7%	2.01 / 87.4%	2.06 / 88.4%
AppE	1.53 / 70.6%	1.14 / 64.9%	1.08 / 60.5%	1.11 / 63.4%	2.26 / 88.9%	2.70 / 96.5%
AuE	0.80 / 65.3%	0.76 / 64.8%	0.49 / 41.5%	0.40 / 33.0%	0.91 / 66.5%	1.60 / 96.8%
AusVE	0.95 / 57.5%	0.76 / 50.7%	0.78 / 57.8%	1.05 / 70.5%	1.53 / 82.9%	1.63 / 91.9%
BahE	2.63 / 70.5%	1.94 / 53.7%	1.76 / 63.4%	2.91 / 76.6%	3.20 / 83.9%	6.22 / 99.5%
EAngE	3.54 / 87.7%	3.08 / 86.1%	2.87 / 90.0%	3.75 / 90.2%	4.58 / 95.9%	5.94 / 99.8%
IrE	2.67 / 91.0%	2.92 / 95.0%	2.49 / 87.8%	1.80 / 78.8%	4.82 / 98.9%	4.53 / 100.0%
Manx	1.86 / 86.8%	1.64 / 86.9%	1.57 / 80.7%	0.84 / 60.5%	2.57 / 95.8%	3.22 / 98.3%
NE-Eng	0.70 / 59.6%	0.77 / 70.5%	0.43 / 38.8%	0.58 / 54.7%	1.43 / 89.9%	1.05 / 77.0%
NZE	2.07 / 84.7%	2.12 / 88.2%	1.48 / 70.3%	2.15 / 85.8%	3.10 / 97.3%	3.48 / 99.4%
NfE	4.17 / 95.4%	3.98 / 96.4%	3.31 / 92.5%	4.3 / 96.7%	5.55 / 98.9%	7.63 / 99.9%
OzE	2.50 / 86.6%	2.73 / 91.9%	2.17 / 85.8%	2.75 / 89.8%	3.59 / 96.6%	4.07 / 99.2%
SE-AmE	2.50 / 79.9%	2.19 / 70.8%	2.03 / 79.1%	2.98 / 84.9%	3.65 / 91.4%	4.72 / 99.6%
SE-Eng	0.20 / 17.4%	0.14 / 13.2%	0.07 / 6.6%	0.22 / 19.7%	0.26 / 22.9%	0.30 / 25.7%
SW-Eng	0.90 / 66.3%	0.77 / 62.9%	0.55 / 43.6%	0.33 / 30.0%	0.84 / 64.4%	1.67 / 96.9%
ScE	1.15 / 69.8%	1.06 / 67.9%	1.06 / 63.5%	0.76 / 51.2%	1.20 / 70.3%	2.05 / 97.8%
TdCE	0.94 / 44.9%	0.69 / 35.9%	0.47 / 31.1%	1.12 / 54.7%	2.17 / 85.8%	2.10 / 92.9%
WeE	2.27 / 90.1%	2.11 / 89.9%	2.51 / 97.1%	1.08 / 61.0%	1.81 / 83.5%	3.01 / 98.7%

Table 16: Average number of features applied per sample and proportion of transformed samples in ESL English.

		MMLU	ARC	TruthfulQA	GSM8K	Hellaswag	WinoGrande
A	ar	2.65 / 96.6%	2.77 / 98.8%	2.05 / 92.6%	3.06 / 99.5%	2.88 / 98.2%	2.87 / 99.8%
	de	2.17 / 93.4%	2.30 / 94.8%	1.92 / 91.8%	2.15 / 94.9%	2.88 / 96.0%	2.98 / 99.7%
	es	3.15 / 97.1%	3.50 / 99.7%	2.74 / 97.1%	3.53 / 99.3%	3.55 / 98.3%	3.63 / 99.6%
	fr	1.00 / 84.6%	0.99 / 86.6%	0.83 / 74.8%	1.15 / 87.2%	1.16 / 87.6%	1.11 / 92.8%
	it	1.03 / 80.8%	1.05 / 87.5%	0.75 / 68.1%	1.20 / 87.3%	1.33 / 89.6%	1.19 / 87.7%
	ja	3.21 / 96.5%	3.41 / 98.8%	2.54 / 94.2%	3.20 / 98.1%	3.93 / 98.1%	3.83 / 100.0%
	pt	2.92 / 98.1%	3.07 / 99.5%	2.89 / 99.4%	3.30 / 99.8%	3.27 / 98.3%	3.36 / 99.9%
	ru	3.02 / 97.5%	3.28 / 99.7%	2.85 / 99.0%	3.53 / 99.5%	3.33 / 98.6%	3.56 / 99.9%
	tr	2.94 / 96.9%	3.08 / 97.9%	2.34 / 92.9%	3.29 / 98.0%	3.18 / 97.6%	3.22 / 99.9%
zh	1.63 / 88.0%	1.67 / 90.6%	1.23 / 83.6%	2.02 / 93.6%	1.77 / 89.6%	1.84 / 93.2%	
B	ar	2.83 / 96.4%	2.82 / 98.2%	2.09 / 91.5%	3.15 / 98.5%	2.84 / 98.8%	2.89 / 99.2%
	de	2.09 / 92.3%	2.01 / 91.9%	1.95 / 91.8%	1.96 / 91.5%	2.54 / 94.7%	2.98 / 99.7%
	es	3.27 / 97.4%	3.43 / 98.9%	2.89 / 97.4%	3.59 / 98.9%	3.30 / 98.8%	3.51 / 99.9%
	fr	0.97 / 83.0%	0.91 / 82.3%	0.79 / 70.2%	1.05 / 84.2%	1.01 / 77.8%	1.11 / 89.2%
	it	0.93 / 73.4%	0.87 / 73.6%	0.65 / 56.2%	1.07 / 79.4%	1.30 / 87.8%	1.21 / 88.5%
	ja	3.31 / 96.6%	3.16 / 98.0%	2.53 / 92.4%	3.06 / 97.9%	3.52 / 98.3%	3.82 / 99.8%
	pt	2.95 / 98.2%	3.05 / 99.0%	2.91 / 99.0%	3.25 / 99.5%	2.94 / 97.2%	3.29 / 99.8%
	ru	3.15 / 97.5%	3.33 / 99.6%	3.01 / 98.6%	3.59 / 99.3%	3.02 / 97.7%	3.52 / 99.9%
	tr	3.06 / 96.2%	2.96 / 96.8%	2.24 / 88.2%	3.26 / 98.5%	3.00 / 98.3%	3.19 / 99.9%
zh	1.83 / 93.3%	1.94 / 97.3%	1.44 / 88.3%	2.2 / 97.8%	1.97 / 96.1%	2.04 / 96.6%	

1174 C.6 Transformation Ratio

1175 Tables 15 and 16 report the average number of features applied per sample and the overall proportion
 1176 of transformed samples for dialect and ESL English, respectively, as discussed in Section 3.4.
 1177 Consistent with the results presented in the main paper, ESL English exhibits a higher transformation
 1178 rate and a greater average number of features applied per sample compared to dialects.

1179 C.7 Human Evaluation

1180 Human annotators were shown one sample at a time, with a total of 150 samples randomly shuffled, 25
 1181 from each model. For each sample, annotators answered two binary (yes/no) questions: (Q1) whether
 1182 the model correctly followed the Qualification and Application steps specified in the transformation

Figure 4: Interface used for human evaluation.

1183 guideline, and (Q2) whether the transformed sentence preserved the original meaning. The interface
 1184 presented to annotators is shown in Figure 4. A sample was considered valid if it received majority
 1185 approval from the annotators.

1186 D Experiments

1187 D.1 Experiment Setting

1188 We evaluated the transformed datasets on seven state-of-the-art models: Qwen2.5-72B-Instruct [63],
 1189 DeepSeek-R1-Distill-Llama-70B [12], LLaMA-3.3-70B-Instruct [23], Gemini 2.0 Flash [20], Gemini
 1190 2.5 Pro [19], GPT-4o-mini [47], and o4-mini [49].¹³ We set the maximum number of generated tokens
 1191 to 2048 and conducted all experiments in a zero-shot setting. The system prompt used was: “Do not
 1192 reason for too long. If the question is a multiple choice question, answer with the option letter. If
 1193 none of the given options match, you may guess or say ‘none of the above.’ Start your final sentence
 1194 with ‘The answer is ’.” To extract the model’s prediction, we parsed the output beginning from the
 1195 phrase “The answer is”, using the subsequent text as the final answer.

1196 D.2 Full Experiment Analysis

1197 Figures 5 and 6 present the full analysis results across all datasets, corresponding to the analysis in
 1198 Section 4.2. Consistent with the findings in the main paper, we observe a positive correlation between
 1199 linguistic distance from Standard American English (SAE) and performance degradation, although
 1200 the strength of this relationship varies across datasets. In ESL English, despite some deviations,
 1201 performance drop generally increases with the difficulty level of the English variety.

¹³Model versions: gemini-2.5-pro-exp-03-25, gpt-4o-mini-2024-07-18, o4-mini-2025-04-16

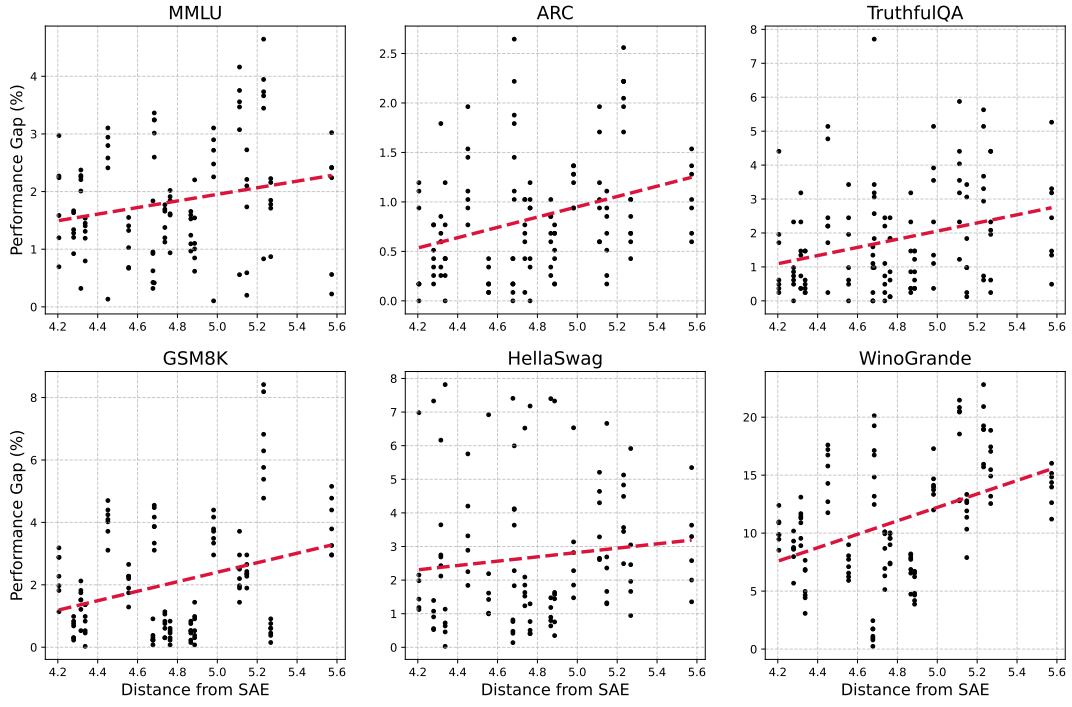


Figure 5: Correlation between linguistic distance and model performance degradation.

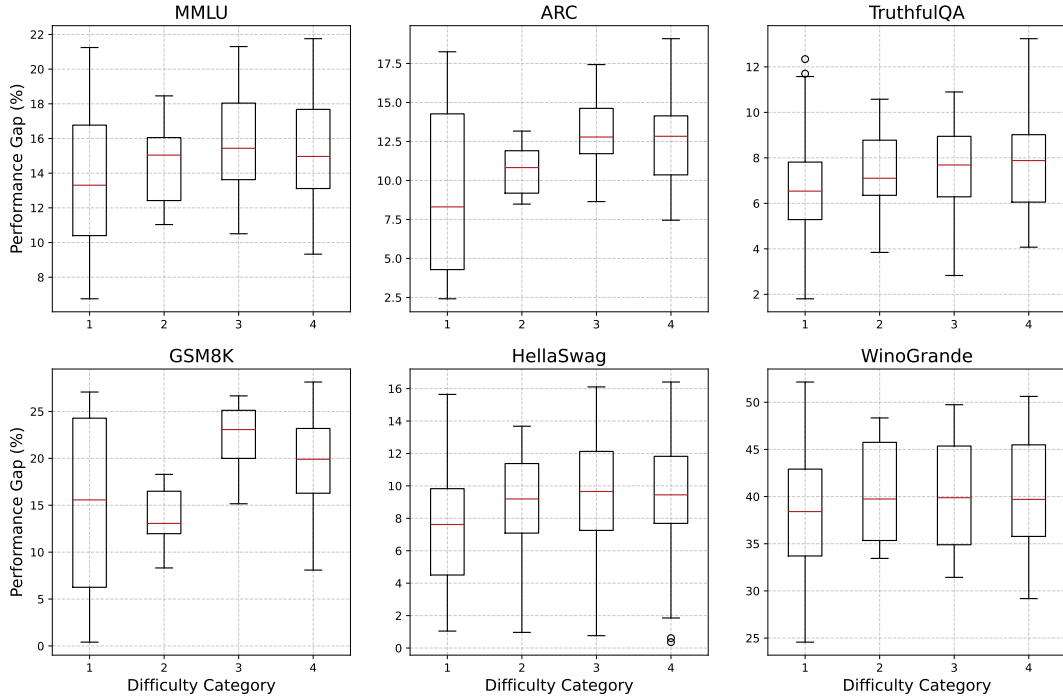


Figure 6: Boxplot by difficulty category and model performance degradation.