What do tokens know about their characters and how do they know it?

Anonymous ACL submission

Abstract
Pre-trained language models (PLMs) that use subword tokenization schemes can succeed at a variety of language tasks that require character-level information, despite lacking explicit access to the character composition of tokens. Here, studying a range of models (e.g., GPT-J, BERT, RoBERTa, GloVe), we probe what word pieces encode about character-level information by training classifier to predict the presence or absence of a particular alphabetical character in an English-language token, based on its embedding (e.g., probing whether the model embedding for "cat" encodes that it contains the character "a"). We find that these models robustly encode character-level information and, in general, larger models perform better at the task. Through a series of experiments and analyses, we investigate the mechanisms through which PLMs acquire character information during training and argue that this knowledge is acquired through multiple phenomena, including a systematic relationship between particular characters and particular parts of speech, as well as natural variability in the tokenization of related strings.

1 Introduction and Motivation
The dominant class of models in NLP (pre-trained transformer models; Brown et al., 2020; Devlin et al., 2019; Bommasani et al., 2021) use tokenization schemes, like BPE or WordPiece tokenization (Sennrich et al., 2015; Schuster and Nakajima, 2012; Kudo and Richardson, 2018), that break text into word pieces. These models face an apparent limitation in that they do not have access to information below the level of the word piece, such as information about characters. But character-level information has been claimed to be useful for a variety of tasks, including adapting text to novel domains like biomedicine, texts with misspellings, and wordplay-based tasks that require attention to character-level manipulations (Riabi et al., 2021; El Boukkouri, 2020; Clark et al., 2021).

Figure 1: Overview of our probing setup. In Experiment 1, the input is a model embedding and we train MLPs to classify whether a particular character (e.g., "a") occurs in a particular token (e.g, "employee"). In Experiment 2, we use syntactic features as input, rather than model embeddings, to train our probe.

But there are drawbacks to using character-level models: character-based sequences are long and therefore can slow down training (Mielke et al., 2021). And giving including character-level information does not necessarily improve performance on tasks where one might expect it to (Libovický et al., 2021; Rosales Núñez et al., 2021; Itzhak and Levy, 2021). Therefore, the vast majority of top-performing models in languages with alphabetic scripts use models with various kinds of subword tokenization schemes (e.g., Devlin et al., 2019; Brown et al., 2020), but rarely with character-level schemes.
One possible explanation for this state of affairs is that models trained on word pieces implicitly learn something about characters, making the explicit inclusion of character-level information unnecessary. Indeed, recent work has shown that even models based on subword tokens might be able to use and manipulate character-level information. Rozner et al. (2021) and Efrat et al. (2021) both study cryptic crosswords and find that PLMs (specifically, T5) can take advantage of character-level information in order to solve wordplay tasks like unscrambling scrambled words. Itzhak and Levy (2021) show that RoBERTa can access subword information by testing it on a spelling task (an F1 score of 93.7 for the best-performing model, e.g., from cat to the characters c + a + t).

The fact that models can do tasks like this is curious: word pieces have no explicit access to character information during training, and the mechanism by which they acquire such information is not obvious. The goal of this paper is to understand the nature of this information, and how it is learned.

Thus, we make several contributions. First, we provide a thorough characterization of what character information is accessible to subword-tokenized PLMs by designing a binary probing task (§3) to probe subword tokens for the presence or absence of a particular character: e.g., does the sequence star contain the letter t? This task lets us not just assess whether this information is available, but lets us characterize, in a fine-grained way, the nature of character-level knowledge in subword tokens. We find performance far above a controlled baseline (an F1 score of 93.7 for the best-performing model, GPT-J), suggesting that subwords learn meaningful information about their characters.

To explore how this information is acquired, we introduce several possible explanations and conduct detailed analyses of the probing task (§3.3). Specifically, we consider how character knowledge varies as a function of the English character being probed for (it’s easier to classify rare letters than common ones), the position in the token of the character in question (performance is somewhat better early in tokens), and the frequency of the token (frequent tokens aren’t necessarily easier to probe). We then turn to the possibility than systematic correspondences between English characters and syntactic features (e.g., adverbs tend to end in "y"), play a role in how models acquire character-level information. To that end, we devise syntactic base-lines, whereby we use features like part of speech as input to the classifier for detecting the presence of absence of tokens (§4). The probe performs much better than control tasks, which suggests syntactic features contribute to the tokenizer’s performance. However, this correlation does not suffice to explain the totality of character information learned by PLMs.

Finally, we consider another possible mechanism, based on the variability of tokenization, by which character-level information might be learned (§5). We conduct an experiment using simple fixed embeddings, as proof of concept that increasing variability in tokenization (Cao and Rimell, 2021) affects the character information learned. Overall, given the importance of tokenization schemes for downstream performance (Bostrom et al., 2021; Mielke et al., 2021), we believe this knowledge could inform the development of tokenization schemes that improve model performance.

2 Prior work

All language models must choose what to use as the basic linguistic unit, and, as a result, there is a long history of work in NLP, evaluating the trade-offs between models that tokenize words based on characters, words, or something in between, like bytes or word pieces (see Mielke et al., 2021; Pinter, 2021, for recent surveys).

While words are a seemingly natural kind and are often used as basic units for modeling language, there is considerable debate in the linguistics literature as to how to even define a word, due to differences across languages (Haspelmath, 2017). Moreover, word-level models have a major weakness in that they do not naturally handle out of vocabulary items (see Jurafsky, 2003, for an overview) and can have very different behaviors in languages with different morphological systems (Mielke et al., 2019; Cotterell et al., 2018). Character-level models have their own weaknesses: they are typically slower to train at the scale required for massive language modeling. Many recent efforts have centered around trying to use meaningful sub-word units in language modeling, such as BPE (Gage, 1994; Sennrich et al., 2015), WordPiece tokenization (Schuster and Nakajima, 2012), and UnigramLM (Kudo, 2018).

While subword tokenization schemes often end up with reasonable linguistic units, they still lack access to character-level information. So there have
been a number of efforts to imbue word or sub
word tokenization schemes with character-level in
formation (Mielke and Eisner, 2019; Kim et al.,
2016; Dos Santos and Zadrozny, 2014; Bojanowski
et al., 2017; Li et al., 2018; Ma and Hovy, 2016;
Aguilar et al., 2020; El Boukkouri, 2020; Clark
et al., 2021). But, if models trained on subword
tokens implicitly learn character-level information
during training, there may be less of a need to sup
plement them with explicit information.

To shed new light on these questions, we use
probing, which is widely used to assess what in
formation is contained in PLM embeddings. (Be
linkov, 2021; Belinkov and Glass, 2019; Hewitt
and Manning, 2019; Hupkes et al., 2018). Be
cause probing has limitations (Elazar et al., 2021;
Pimentel et al., 2020; Voita et al., 2021), we use a
number of control tasks (Hewitt and Liang, 2019)
and baselines in order to ask what can be recovered
from embeddings, relative to a control of equal
expressive power.

3 Experiment 1: Probing for character
information

The main goal of our first experiment is to quan
tify the extent to which tokens in PLMs capture
character-level information and characterize that
knowledge across a variety of dimensions. We
train a binary classifier probe that takes as input a
token’s frozen embeddings from a PLMs to predict
whether a particular character of the English alp
abet is contained in that token. That is, if successful,
the probe will predict that *cool* contains an "o" but
"cat" does not. We also consider a task in which
the probe must say whether one token (e.g., "coo")
is a substring of another token (e.g., "cool"). We
examine the probe’s success as a function of the
character being probed for, length of the token be
ing probed, position of the character in the token,
and frequency of the token.

3.1 Method

We consider the static non-contextualized embed
dings of PLMs: GPT-J (Wang and Komatsuzaki,
2021), GPT-2 (Radford et al., 2019), RoBERTa
(Liu et al., 2019), BERT (cased and uncased; De
vlin et al., 2019), as well as GloVe embeddings
(Pennington et al., 2014) and Language-only em
beddings of the multimodal LXMER T (Tan and
Bansal, 2019). See Appendix B for model details.

Each language model has its own vocabulary,
consisting of tokens. We consider only the tokens
consisting entirely of characters in the standard En
glish alphabet (a-z), along with the special charac
ters that accompany these tokens, such as preceding
whitespace (denoting by `G` in the RoBERTa and
BERT-family) or symbols denoting continuations of
preceeding word (`#` in BERT family).

Our probing task trains classifiers to detect
the presence or absence of each of the 26 En
glish alphabets α over each token w from the
filtered-vocabulary V. Thus, a separate dataset
for each alphabet α is constructed over V as

\[ D_α = \{(w_1, y_1), (w_2, y_2), \ldots (w_d, y_d)\} \]

where the binary label \( y_i \) denotes whether α occurs at least once in
\( w_i \in V \). From these data-points in \( D_α \), we create a balanced dataset \( D_α \) with equal number of positive
and negative labels by undersampling the \( (w_i, y_i) \)
points with \( y_i \) as the negative label (i.e., when prob
ing for the presence of the character "z", half the
tokens will contain "z" even though most tokens
in general do not). We then split \( D_α \) into training
and test splits in a roughly 80-20 ratio, while en
suring that tokens with the same lemma appears in
the same split. This is the most challenging split,
as it prevents the probe from leveraging wordform
similarity across words with the same lemma in
both training and test (I tzhak and Levy, 2021).

We train our probe over the static non-trainable
embeddings \( E \) of these PLMs. For a data-point
\( (w_i, y_i) \), the probe receives as input a token \( w_i \).
The probe predicts logits \( \hat{y}_i \) by an MLP:

\[ \hat{y}_i = \sigma(MLP_α(E^Tx_i)) \]

In the control task, we consider randomly-initializa
ted non-trainable embeddings instead of the trained
embeddings from the PLMs.

Substring Sub-experiment As an additional sub
experiment for assessing the generalizability of
the task, for the best-performing model (GPT-J),
we consider a related substring classification task.
Specifically, we probe GPT-J’s embeddings to detect
whether a token \( u \) is a substring of the token \( v \). That
is, can it detect that the token "ome" is a substring
of "some"? For this condition, we set up the experi
ment as before but, rather than attempt to detect the
presence or absence of a character, we seek to clas
sify whether a particular token \( u \) is a substring of
another token \( v \). To create positive examples, we
consider all substrings of \( v \) that are in the overall
vocabulary \( V \). For each positive example, we sam
ple a token from \( V \) of equal character length as \( u \),
which is *not* a substring of \( v \) in order to create neg
ative examples. This creates a balanced set, from
Figure 2: For selected models, the average F1-score (y-axis) for how well a character (x-axis) can be classified on our main probing task. The control (random embeddings) appears in red, the syntax baseline in green, and the 4 models shown in grayscale, with the largest and most recent model (GPT-J) in the darkest color.

which we sample an 80-20 train-test split, ensuring that the superset token \(v_i\) always occur in the same split. We train the probe as before, with the input as the concatenated embeddings of the two tokens.

### 3.2 Results

#### Main Character Probing Results

Table 1 shows the results averaged across 5 train-test splits and different seeds, reporting on the Macro-F1 metric averaged across all 26 characters. We also observe very low variance for the strong performing models, as shown in the Appendix (Table 6).

For our main character probing experiment, all models perform substantially better than their matched controls (which hover around 50, which is chance level), suggesting that word piece tokens from PLMs store information about their constituent characters in their embeddings. GPT-J is the best-performing model (with F1 of 93.70 and 94.35), followed by RoBERTa and GPT-2, then the BERT models. All the transformer models outperform the GloVe fixed embedding model. Clearly, the performance of the models on this probing task correlates with performance on other language tasks, such that larger models trained on larger corpora do better.\(^1\)

There are also other factors that may contribute to difference in performance such as the nature of the pre-training task and the tokenizer. The latter is evidence from the considerable performance gap between RoBERTa and BERT, which may be partially attributed to RoBERTa using GPT’s reversible tokenizer, leading to more variability depending on preceeding whitespace. (See §5 for the potential effect of tokenizer variability on performance.)

#### Substring Experiment

Performance on the Substring Experiment is also far above chance, with an average F1 of 86.56, compared to a control F1 (on random embeddings) of 70.03 (bottom row in Table 1). Control performance is well above 50 in this case since the data set is created to be balanced such that the superstrings have equal numbers of positive and negative examples. But there are still baseline differences in how often a token occurs as a substring, so the model can learn that certain substrings like "en" are more common than substrings like "emies". We take the performance on the Substring Experiment as evidence that the model can make use of character information to do more complicated substring tasks than just character identification.

### 3.3 Breakdown of results

Next, we consider a number possibilities for how character-level information gets into these embeddings and conduct analyses intended to understand the nature of the information learned and how it gets there.

Is the first letter learned best because of alphabetization? One possibility is that, because the training data likely contains many alphabetical lists and other kinds of word lists (e.g., lists of words starting with "z"), the model learns a co-occurrence relationship between words that start with the same character. We would predict that this would cause stronger performance when the probed character

### Table 1: Results for the main probing experiment.

| Model type  | PLM     | Control |
|-------------|---------|---------|
| **Main Probing Experiment** |         |         |
| GPT-J       | 93.70   | 48.36   |
| GPT-2       | 84.25   | 52.31   |
| RoBERTa     | 86.41   | 47.33   |
| BERT-Cased  | 78.50   | 47.08   |
| BERT-Uncased| 77.48   | 49.37   |
| GloVe 300D  | 66.04   | 50.33   |
| GloVe 100D  | 67.57   | 49.57   |
| LXMERT      | 62.4    | 53.92   |
| **Substring Sub-Experiment** |         |         |
| GPT-J       | 86.56   | 70.03   |
occurs at the beginning of the word. To that end, we examine how the model’s performance varies as a function of where in the token the target character is (top panel in Figure 3). While there is indeed a significant negative relationship between word position and recall as measured by a linear regression ($\beta = -.01$, $p<.001$), the slope is relatively small. While recall on the first letter in a token is high (95.2), it is not an outlier: performance is only somewhat higher than recall for the second character (94.5). Moreover, performance is above chance even when the target character appears 10 or more characters deep in a token. Therefore, we do not believe the effect is driven only by word beginnings, although they likely play a role.

Is it only frequent words that the probe gets right? Next, we consider whether performance varies as a function of the frequency of the token (middle panel in Figure 3). One possibility could be that character information is memorized only in high-frequency tokens like “the”, which occur often enough that at least some of the time very frequent token will occur broken down into characters (e.g., “the” appearing in the context of “t h e”), and that low-frequency tokens will perform worse. This does not appear to be the case and, in fact, there is, if anything, a negative relationship ($\beta = -.013$, $p=.05$) between binned log frequency and performance, such that less frequent tokens are easier to attain character information from.

Is it easier to get long or short words right? The bottom panel of Figure 2 shows F1-score as a function of the length of the token. Using the GPT-J embeddings, it is easier to classify characters in short tokens, as compared to longer tokens. This may be a function of the nature of the task since there is, in some sense, less information to be represented for a short token like "be" for the purposes of the task (just that it contains a "b" and it contains an "e"), whereas a long token would have to represent information about more characters.

Which characters are learned best? Part of what makes the success of the probe is that word embeddings represent word co-occurrence information, which is typically conceived of as syntactic and semantic in nature (Erk, 2016) and so should, because of the arbitrariness of the relationship between forms and meanings (Saussure, 1916; Hockett, 1960), mean there is no relationship between individual characters and information learned by embeddings. But this arbitrariness breaks down, in that there are statistically detectable non-arbitrary form-meaning relationships in language (Blasi et al., 2016; Monaghan et al., 2014; Tamariz, 2008; Dautriche et al., 2017; Pimentel et al., 2019), such as the fact that fl- words in English tend to be about movement (e.g., flap, fly, flutter, flicker; Marchand, 1959; Bergen, 2004) and that different parts of speech have different phonological patterns (Dautriche et al., 2015; Kelly, 1992; Monaghan et al., 2005). An even larger source of shared information between characters and syntactic/semantic information is that morphological forms can be cues to word categories: for instance, most plural nouns end with "s" and many adverbs end in "ly". This leads to changes in character-level distributions: while roughly 12% of words in American English contain "y", 85% of adverbs do (as estimated using data from Brysbaert et al., 2012). Thus, a model with access to part of speech information could do well by guessing that all adverbs contain "y".

So one possibility is that the probe’s performance is largely driven by characters that correlate with syntactic and semantic features. If this were the case, we might expect some characters to show much better performance than others. Figure

![Figure 3: Performance on the GPT-J probe, relative to a control probe, as a function of the character’s position in the token (top), the log frequency of the token (middle), and the length of the token (bottom). The size of the point reflects the amount of data.](image-url)
Table 2: The best and worst performing characters from Experiment 2 on the SpaCy syntactic baseline, the GPT-J syntactic baseline, and the Control.

| Measure          | SpaCy | GPT-J | Control |
|------------------|-------|-------|---------|
| Aggregate Performance |     |       |         |
| F1               | 52.34| 61.24 | 49.68   |
| Best performing characters |     |       |         |
| s                | 64.60| 66.82 | 40.32   |
| y                | 61.96| 64.89 | 48.68   |
| e                | 62.05| 62.32 | 47.27   |
| Worst performing characters |     |       |         |
| b                | 43.79| 53.54 | 49.28   |
| m                | 48.13| 55.61 | 46.11   |
| q                | 43.79| 53.54 | 49.28   |

2 shows the F1-Macro as a function of character. For GPT-J, the best-performing model, there are some clear trends. For instance, it is easiest to classify rare letters: J, W, X, Q, Z all have F1-scores over 93. And it is hardest for the probe to classify vowels: U, A, O, and E are the lowest performing characters between 83 and 86. But even those lower-performing characters do far better than the chance baseline (at about 50 F1 score).

To further explore this, we conducted a qualitative analysis of the probe’s successes and failures. Consider the probe for classifying the presence/absence of "y": the model assigns highest confidence to the following 4 tokens: "ily", "selectively", "subly", "mechanically". These all have "ly" endings, which in English is typically associated with adverbs. Similarly, the top performing tokens for the "s" classifier all end with a morphologically meaningful "-s" suffix: "socialists", "stocks", "suggestions".

This analysis suggests that the strong classifier performance could be explained by the model learning systematic relationships between certain characters and syntactically or semantically meaningful morphology. Is syntactic information the window through which character-level information enters PLMs? To address that question, our next experiment focuses on a syntactic baseline, to see how well character-level information can be predicted based on syntactic features.

4 Experiment 2: The effect of syntactic information

In this experiment, we focus on building probes for the same task as in Experiment 1 (identifying whether a particular character occurs in a particular token). But, rather than using the token embeddings from a large language model as input, we attempt to classify the presence/absence of characters in a token based on syntactic information.

Our first model (the SpaCy model) uses SpaCy (Honnibal and Montani, 2017) to obtain distributions over features for each token in the vocabulary: Fine-Grained Part of Speech tag (PoS; e.g., for "Jane", NNP for a proper noun), Coarse-Grained Part of Speech tag (Coarse-grained PoS; e.g., for "Jane", PROPN for proper noun), and a Named Entity Recognition tag (NER; e.g., for "Jane", PERSON for a personal name). We use these features to construct a syntactic vector for each token.

Because SpaCy is built to operate over words, not tokens, we also construct custom syntactic baselines that can tag subwords, as opposed to tokens.

The performance of these probes will serve as a baseline for ascertaining how much character-level information can be learned by these features alone, without a full language model. If they can perform just as well as the full GPT-J embeddings, that would suggest that morphosyntactic information (of the sort that we already know is learned by PLMs during pretraining) is sufficient for the performance on the probing task.

The method is the same as in Experiment 1, where the goal is to predict the presence or absence of a character α in a token, except that instead of using the token’s model embeddings as input, we instead use syntactic feature vectors (obtained either from SpaCy or a custom tagger) as input. We describe these syntactic vectors below.

Syntactic baselines The SpaCy model has 3 features for each token: NER, PoS, and Coarse-Grained PoS tags. The resultant features are discrete one-hot feature vectors over labels.

The custom syntactic tagger, which solves the problem that SpaCy tags words, not subword tokens, takes a (subword) token’s model embedding as input and outputs a vector of probabilities over part of speech and named entity categories. Here, we describe results for our custom GPT-J Tagger, trained using GPT-J model embeddings, since GPT-J is the best-performing of our models for our main task. See Appendix C for descriptions and the results for 2 additional BERT-based custom taggers that we built.

To build our custom GPT-J-Tagger, we train an MLP model to predict PoS and NER label based on GPT-J’s static embedding layer for each token. The tagger is trained on the CoNLL 2003 dataset’s train and valid splits (Sang and De Meulder, 2003),
which contains part of speech and named entity information. Unlike the SpaCy tagger, our custom GPT-J-Tagger outputs a probability distribution over categories. We use this distribution over labels as input, rather than a one-hot vector. In the Appendix, Table 10 shows the performance of the tagger’s performance qua tagger.

Probing for characters using syntactic baselines
We run the character probing experiment as before. But, rather than using the model embeddings, we use the syntactic feature vectors as the target of our probe. Table 2 shows the results of these experiments. Using the syntactic baselines leads to substantially improved performance over control tasks, and the GPT-J-Tagger does better than the SpaCy tagger. We hypothesize that this is because the custom GPT-J-Tagger is better suited to handling subwords, and because it enables us to use label distribution rather than one-hot vectors. Zooming in on the performance over individual characters, we observe that some English alphabets consistently perform much better when using the syntactic features, than the control task. As predicted, these are precisely the characters that are highly correlated with particular parts of speech. The best performing characters are: "s" (associated with plural nouns and third-person singular verbs) and "y" (associated with adjective and adverb endings). Thus, the syntactic baselines seem to be capturing the information that they were intended to capture. But their performance still fell far below the best performing PLMs, suggesting that the large models are capturing more than just the information captured by the syntactic models. Moreover, as can be seen in Figure 2, the syntax baseline shows a sharp peak for morphologically informative characters like "s", but this pattern is much weaker in GPT-J (which shows only a slight performance increase for "s"). Therefore, we do not think syntactic information can explain all the character information learned by PLMs. In the next section, we consider another possibility: variability of tokenization, the focus of the next section.

5 Experiment 3: Tokenization variability
Here, we posit that the variability of tokenization is another avenue by which character-level information could be learned by models. We first quantify this variability and then run an experiment using CBOW Word Embeddings (Mikolov et al., 2013) showing how increasing the variability in tokenization can lead to more character information being learned.

Subword tokenization like the one used by GPT models can cause the same lemma to have very different tokenizations, depending on its form and/or its spelling. See Table 3 for possible tokenizations of "dictionary" and related forms, including a misspelling (bottom row). This is a subset of the possible misspellings, variants, and morphological forms of the word. But the listed forms alone generate 8 unique tokens.

It would be useful for the model to learn a relationship between all these tokens, since they represent the same lemma. We posit that the desirability of learning this mapping is a mechanism by which character information could be learned, by inducing an objective to map between atomic tokens like ‘dictionary’ and the various substring tokens that can arise. While each of these mappings could be learned individually, learning character-level spelling information offers a more general solution to the problem, such that even a completely tokenization could be interpreted by composing characters.

For this to be plausible, though, variable tokenizations like this must be frequent enough for it to matter. In Appendix D, we use heuristics to identify different forms in which a word appears and conduct a series of back-of-the-envelope calculations to determine how many different unique tokenizations are expected for a long word (8+ characters) like dictionary, in all its variant forms and misspellings in a sample of the Pile corpus (we used 1/6 of the corpus as a sample; Gao et al., 2020). We found that, on average, we should expect over 200 different tokenizations for a word like "dictionary", many of which have no tokens in common.

This result leads to a prediction: increasing the variability of tokenization should increase the amount of character-level information learned. To test this, we train models using tokenization schemes with different levels of variability and then test how much character-level information they learn, using our probing task.
| Tokenization | $\rho$ | Embedding | Control |
|--------------|--------|-----------|---------|
| Word         | -      | 60.55     | 47.12   |
| GPT-J        | -      | 63.23     | 47.51   |
| GPT-J        | 0.05   | 66.00     | 47.23   |
| GPT-J        | 0.1    | 65.64     | 46.72   |
| GPT-J        | 0.2    | 64.23     | 47.01   |
| GPT-J        | 0.5    | 62.33     | 46.47   |

Table 4: Average F1 scores for probing results, as a function of change in tokenization variability

Because the overall goal of our paper is to characterize and explain the nature of character-level information learned, and not to use it to build a better model, we conduct a proof-of-concept experiment using CBOW Word Embeddings (Mikolov et al., 2013) on a portion of the Pile corpus with 1.1B characters, as opposed to training a large transformer model from scratch varying tokenization schemes. We train 6 CBOW models from scratch, each with a different tokenization scheme. As baselines, we consider vanilla rule-based word-tokenization (the CBOW default, labeled "Word" in Table 4) and GPT-J’s default word piece tokenization scheme. Comparing these two baselines against each other lets us compare the effect of word tokenization vs. subword tokenization on character information. But our key manipulation is to consider variations of GPT-J’s tokenizer in which we systematically increase tokenization variability. In pre-processing the word-tokenized corpus for input, for each word token $w_i$, with probability $(1 - \rho)$, we tokenize it using the standard GPT-J tokenizer. Under the standard tokenizer, "schematics" becomes "sche + mat + "ics". With probability $\rho$, however, we tokenize $w_i$ using a random tokenization that consists of alternative valid tokens from GPT-J. So, "schematics" could become "schema + tics" or "schematic + s" (but not "schemat + cs" since "schemat" is not a valid GPT token). We vary $\rho$ from 0.05 to 0.5. See Appendix D for more details on this procedure. The result is a series of tokenized corpora, which have more variable tokenization than the vanilla GPT-J-tokenized corpus.

We train CBOW models, separately for each of these corpora. Table 4 shows the results of these experiments on our probing task (using the same method as in Experiment 1). As expected, probes on the subword tokenization schemes reveal they learn more information about characters than the default word-level tokenizer. Most importantly, upon increasing the variability on GPT-J’s tokenization scheme, the performance of the probe increases, peaking at $\rho = 0.05$ and $\rho = 0.1$. Thereafter, the performance decreases with variability, suggesting that increasing variability leads to increased character knowledge but only up to a point, like because there is a tradeoff: since the corpus size for the toy experiment is small, having very high variability leads to the model seeing fewer instances of each token.

While the magnitude of these differences are relatively small, they are consistent across random seeds and train-test splits. Thus, we believe that these results offer proof of concept that (a) the variability of tokenization affects how much character information is learned by PLMs and (b) that increasing tokenization variability could be a means by which PLMs could be built to learn more character-level information.

## 6 Discussion and Conclusion

Overall, our results suggest a possible explanation for why efforts to infuse subword models with character-level information may not be necessary: the information already gets learned during training through a variety of methods. Insofar as these methods (e.g., tokenizer variability) can be manipulated in model construction, this knowledge could be used to build models that perform better at tasks dependent on such knowledge. In future work, we believe it will be important to test the generalizability of these results in languages other than English. Given the particular importance of tokenization in multilingual models (Rust et al., 2021; Singh et al., 2019), it would be fruitful to consider these results in multilingual settings.

More generally, while the linguistic capabilities of PLMs are much studied (Rogers et al., 2020; Bommasani et al., 2021), the question whether PLMs learn the constituent characters of tokens is of a different nature in that it depends on learning a property of language (spelling) that is not explicitly tied to meaning. There is no a priori reason "dog" is spelled "D-O-G", and, in a sense, the spelling of the word does not matter. But, in another sense, it *does* matter: humans routinely use language in creative and character-dependent ways: e.g., alphabetizing text, scrambling letters to create codes, and solving crossword puzzles. Understanding whether the building blocks of this knowledge can emerge during self-supervised training on a word prediction task could be of interest not just in NLP, but in the cognitive sciences.
7 Ethics and Broader Impacts

This work consists of probing experiments and interpretability analyses of PLMs, and the risks and ethical considerations are largely those that affect any work with large PLMs (e.g., energy costs; see Bommasani et al., 2021, for an overview of risks and tradeoffs). The intended use of our code is for academic research. We consider probing publicly available PLMs, which are made publicly available in part for research purposes, to be within the intended use of PLMs.

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Appendix A  Code details

We release our code anonymously at https://github.com/Anonymous-ARR/code under MIT License.

The models weights, data and other dependencies required for experiment are at https://github.com/Anonymous-ARR/Releases/releases.

The intended use of our code is for academic research. We consider probing publicly available PLMs, which are made available for research as well as end use cases, to be within the intended use of PLMs.

Appendix B  Probing for Character Information

We use off-the-shelf APIs for lemmatization and WordNet from NLTK (Bird et al., 2009) (Apache License 2.0). Our implementation uses PyTorch (Paszke et al., 2019) (BSD License), HuggingFace (Wolf et al., 2019) (Apache License 2.0) and custom APIs for GPT-J’s embedding.

The probes for each MLP are trained separately starting with random initialization weights. We train the probe via a binary classification task via backpropagation, using the Adam optimizer (Kingma and Ba, 2014) with betas of 0.9 & 0.999 and epsilon of 1e-08 without weight decay, over the standard Binary Cross Entropy loss across the predicted logits \( \hat{y}_i \) and ground truth logits \( y_i \).

B.1  PLMs considered

Details of the PLMs used along with their model-card on Huggingface:

| Model type       | Case-Sensitive | PLM | Control |
|------------------|----------------|-----|---------|
| GPT-J            | 94.35          | 52.76 |
| GPT-2            | 84.69          | 51.05 |
| RoBERTa          | 83.87          | 49.00 |
| BERT-Cased       | 78.47          | 45.35 |
| BERT-Uncased     | 77.48          | 49.37 |
| GloVe 300D       | 69.40          | 49.40 |
| GloVe 100D       | 61.56          | 49.55 |
| LXMERT           | 60.30          | 49.61 |

Table 5: Results for the main probing experiment, across models.

- **GPT-J**: We used the standard GPT-J with 6 Billion parameters and its reversible Byte-Pair encoding based subword tokenizer. We extracted the embeddings and have released it separately. Model Card: ‘EleutherAI/gpt-j-6B’ under Apache 2.0 License.
- **GPT-2**: We consider the base model for GPT-2 with 124 Million parameters. The tokenizer used in this model is the exact same as the one used in GPT-3 and is also a subword tokenizer based on reversible Byte-Pair encoding. Model Card: ‘gpt2’ under Modified MIT License.
- **RoBERTa**: We again use the Base model for fairer comparison to GPT-2 model with 125 Million parameters. This model has partially reversible Byte-Pair Encoding based on GPT-2’s byte-pair tokenizer but with additional tokens for a BERT-like MLM discriminative pre-training. Model Card: ‘roberta-base’ under MIT License.
- **BERT**: The BERT-base models have roughly 110 Million parameters. Both the Uncased and Cased versions of this model are considered with their Word-Piece tokenizers. For this tokenizer, we also consider the character ‘##’ while filtering out vocabulary, as it denotes the token continues on the preceeding word. Model Card: ‘bert-base-uncased’, ‘bert-base-cased’ under Apache 2.0 License.
- **GloVe**: We experiment with 100 and 300 dim version of 400K-Vocab GloVe trained on 6B tokens. We consider the 40k most frequent tokens in GloVe, comparable to the vocabulary sizes of the other models. GloVe version used: ‘Wikipedia 2014 + Gigaword 5 (6B tokens, 400K vocab, uncased, 50d, 100d,
200d, & 300d vectors, 822 MB download):
glove.6B.zip \(^2\)

- **LXMERT**: We use the uncased version of
LXMERT-base model and similar to the
BERT model, filtering out also for ‘##’ preceding
symbols. Model Card: ‘unc-nlp/lxmert-
based-uncased’ under

### B.2 Hyperparameter and other Details

Each probe is trained for 5 epochs, with 128 batch-size. The Learning rate is tuned over averaged
Macro-F1 in the grid \(\{1e-5, 3e-5, 5e-5, 1e-4, 3e-4, 1e-3, 3e-3, 1e-2, 3e-2\}\). We
trained the probe on the best hyperparameter sett-
ings across 5 different train-test splits and seeds.
Table 8 shows these best learning rate and the num-
er of parameter (and frozen-parameters) in the
probe. For all the control embedding, we assume
the same dimension as the largest model (4096)
and considered a maximum vocab of 100k, even
though only the first few thousands might be used.
These experiments take less than 20 minutes for
each run requiring less than 12 GB of GPU mem-
ory and were run on a mix of NVidia Tesla K80,
GTX 1080 Ti, P100, V100 GPUs with Dell R740
and Intel Xeon CPUs.

Table 5 shows the result of the probe in a case-
sensitive setting. The case-insensitive probe treats
both "Cat" and "cat" as a hit for both "c". The
case-sensitive probe treats only "cat" (not "Cat")

\(^2\)Accessible at nlp.stanford.edu/projects/glove/. Apache
v2.0 License

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**Table 6: Standard Deviation in our probing experiment 1 for the key models considered.**

| Model       | Case-insensitive | Case-Insensitive |
|-------------|------------------|------------------|
|             | PLM              | Control          |
| GPT-J       | 0.83             | 3.12             |
| GPT-2       | 2.01             | 3.09             |
| RoBERTa     | 2.27             | 3.13             |
| BERT-Cased  | 2.93             | 7.46             |
| BERT-Uncased| 3.32             | 4.33             |

**Table 7: Dataset Checklist for experiment 1.**

| Property      | Statistics                        |
|---------------|-----------------------------------|
| Dataset       | Tokenizer’s Vocab for each model |
| Data-filtered | Tokens having only letters (a-z,A-Z) |
|               | GPTs, RoBERTa: Allow preceding G  |
|               | BERT: Allow preceding ‘##’        |
| Train-Test split | 80-20                             |
| Preprocessing  | None                              |
| Output labels | 26 tasks (each with binary label) |
| Link          | Model Card & links in §B.1        |

**Figure 4: Experiment 2: syntax baselines with BERT-sentence and BERT-token custom taggers.**

as a hit for "c". Note that performance is the same
for BERT-Uncased since it does not distinguish
between these conditions.

**Appendix C Syntax Baseline for Character information**

**C.1 Custom syntax taggers**

First we consider an off-the-shelf SpaCy model
with its 3 features for each token: NER, PoS, and
Coarse-Grained PoS tags. Before running this
model, we remove the preceding whitespace char-
acters in the token, if present. The resultant features
are discrete one-hot feature vector over labels. The
SpaCy tagger is not perfectly suited to our task
since it operates at the word level, whereas we are
concerned with obtaining a subword token’s em-
beddings. To solve that problem, we also built
3 custom taggers for obtaining PoS and NER la-
beLS on subword tokens. These tagger takes (a
subword) token’s model embedding as input and
outputs a vector of probabilities over part of speech
and named entity categories.

To build our custom GPT-J-Tagger, we train an
MLP to predict PoS and NER label based on GPT-J’s
static embedding layer for each token. The
tagger is trained on the CoNLL 2003 dataset’s
train and valid splits (Sang and De Meulder, 2003),
which contains part of speech and named entity
information. Unlike the SpaCy tagger, our custom
GPT-J-Tagger outputs a probability distribu-

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In addition to the BERT sentence-level tagger, we consider a BERT token classifier model fine-tuned for NER and PoS at token level rather than at sequence (sentence level) in the preceding one with same pre-processing. This token-level model does not leverage context to deduce the label, and is closer to how we use this model later to get features for predicting NER/PoS features.

### C.2 Results and Hyperparameters

We use off-the-shelf APIs for lemmatization and WordNet from NLTK. Our implementation uses PyTorch (Paszke et al., 2019), HuggingFace (Wolf et al., 2019) and custom APIs (now released) for GPT-J’s embedding. The hyperparameter tuning was done on the dev set for only the learning rate in the grid \{1e−5, 3e−5, 1e−4\} for BERT and \{1e−5, 3e−5, 5e−5, 1e−4, 3e−4, 1e−3, 3e−3, 1e−2, 3e−2\} for GPT-J. Our MLP model is 3-layered with SELU and Tanh activation and 0.1 Dropout before the last layer. Our BERT-Model is initialized with ‘bert-base-cased’ from Huggingface with default values of hyperparameters. Our implementation was done using PyTorch and optimized via Adam with betas of 0.9 & 0.999 and epsilon of 1e-08 without weight decay over the standard Cross Entropy loss. We set the batch size to 32 sentences for BERT and 64 for GPT-J. All the experiments can be done within 16GB of GPU memory and no run individually takes more than 2 hours. We release these models along with our codebase with instructions to run them.

Table 10 shows the performance of these NER and PoS models. As expected, the BERT-sentence model performs the best on both the tasks as it leverages the context while tagging. Whereas, GPT-J slightly outperforms BERT-token on both the tasks. Note that these performance are not comparable as their tokenization differ and only one of the model leverages context to predict NER and PoS tag.

### C.3 Method

Assume we have \( m \) syntactic features. Consider the tokenizer Vocabulary \( V \) (with only alphabetic tokens) and the \( D_{\alpha} \) datapoint pairs for each letter \( \alpha \) of the lowercased English alphabets. For each token-label pair \((w_i, y_i)\), we obtain the \( m \) syntactic features of the word \( \{x_i^{(1)}, x_i^{(2)} \ldots x_i^{(m)}\} \) using the trained models to tag the features.
| Model Type               | # Epochs | Batch Size | LR  | Dev $F_{1\text{Wtd}}$ | Dev $F_{1\text{Macro}}$ | Test $F_{1\text{Wtd}}$ | Test $F_{1\text{Macro}}$ |
|-------------------------|----------|------------|-----|------------------------|--------------------------|------------------------|--------------------------|
| BERT-sentence (PoS)     | 10       | 32         | 1e-5| 98.17                  | 94.80                    | 93.42                  | 87.40                    |
| BERT-token (PoS)        | 10       | 32         | 1e-5| 76.42                  | 56.75                    | 77.24                  | 56.74                    |
| GPT-J MLP (PoS)         | 20       | 64         | 1e-4| 62.90                  | 68.72                    | 60.15                  | 69.14                    |
| BERT-sentence (NER)     | 10       | 32         | 1e-5| 97.88                  | 93.18                    | 96.02                  | 86.92                    |
| BERT-token (NER)        | 10       | 32         | 1e-5| 83.50                  | 56.97                    | 81.57                  | 54.88                    |
| GPT-J MLP (NER)         | 20       | 64         | 5e-5| 85.59                  | 63.56                    | 82.71                  | 57.34                    |

Table 10: Labels from POS/NER labels. LR denotes learning rate.

| Split Type | SpaCy | BERT-sentence | BERT-token | GPT-J | Control |
|------------|-------|---------------|------------|-------|---------|
|            |       | Aggregate across 26 characters |            |       |         |
|            |       | F1            |            |       |         |
|            |       | 52.338        | 59.108     | 61.2395 | 49.672  |
|            | Best performing ones | 70.3299     | 66.8159    | 40.3154 |         |
|            |       | s             | 64.5967     | 60.7179  | 70.3299 |
|            |       | y             | 61.9632     | 60.3871  | 67.1591 |
|            |       | e             | 62.0518     | 57.7531  | 64.6152 |
|            |       | t             | 60.6848     | 54.3826  | 64.0681 |
|            |       | p             | 50.235      | 55.2361  | 63.9658 |
|            |       | i             | 60.8024     | 56.4055  | 63.3518 |
|            | Worst performing ones | 57.6919     | 55.7508    | 48.6947 |         |
|            |       | w             | 45.748      | 52.7235  | 57.6919 |
|            |       | q             | 43.7924     | 56.5274  | 57.5407 |
|            |       | k             | 47.7873     | 49.3832  | 57.3084 |
|            |       | o             | 52.9403     | 53.6138  | 56.8312 |
|            |       | b             | 48.9159     | 56.739   | 56.2846 |
|            |       | m             | 48.1349     | 53.4036  | 56.2846 |

Table 11: Syntax baseline: Probing over syntax label distribution.

| Split Type | SpaCy | BERT-sentence | BERT-token | GPT-J | Control |
|------------|-------|---------------|------------|-------|---------|
|            |       | Aggregate across 26 letters |            |       |         |
|            |       | F1            |            |       |         |
|            |       | 4.4354        | 2.9588     | 3.7989 | 2.724   | 4.3973  |
|            | Best performing ones | 1.2941      | 1.6406     | 1.4251 | 1.3417  |         |
|            |       | s             | 0.6947      | 1.2941  | 0.4853  | 0.6314  | 5.0555  |
|            |       | y             | 1.8665      | 1.6406  | 0.5697  | 1.4251  | 3.2417  |
|            |       | e             | 0.6645      | 0.8544  | 0.3245  | 0.3233  | 1.8349  |
|            |       | t             | 0.2643      | 3.4695  | 0.9129  | 0.5924  | 1.7645  |
|            |       | p             | 6.1928      | 1.1628  | 0.5669  | 0.2985  | 3.7013  |
|            |       | i             | 0.512       | 1.4392  | 0.5998  | 0.4867  | 5.5685  |
|            | Worst performing ones | 2.596       | 4.5954     | 1.9536  | 1.7453  |         |
|            |       | w             | 4.9794      | 2.596   | 1.9614  | 1.9536  | 1.7453  |
|            |       | q             | 2.7071      | 3.4438  | 4.5954  | 4.7932  | 5.5068  |
|            |       | k             | 2.9332      | 6.885   | 2.0885  | 1.6864  | 1.6311  |
|            |       | o             | 6.24        | 1.6009  | 1.0449  | 0.463   | 3.5961  |
|            |       | b             | 4.0455      | 1.5597  | 1.4074  | 2.0701  | 2.7857  |
|            |       | m             | 7.2995      | 2.4854  | 2.1762  | 1.0948  | 6.152   |

Table 12: Standard Deviation of POS/NER labels.
We train a classifier to predict whether a character $\alpha$ is present in the token $w_i$ using only its syntactic features. Assume randomly initialized ‘trainable’ embeddings $\{E_1, E_2, \ldots E_m\}$ for each of the $m$ syntactic features. We predict the logits $\hat{y}_i$ for token $w_i$ over each letter $\alpha$ using an MLP classifier over the embeddings:

$$\hat{y}_i = \sigma(MLP_\alpha([E_1^T x_i^{(1)}; \ldots; E_m^T x_i^{(m)}]))$$

where $T$, $\sigma$, $;$ denotes transpose, sigmoid function and vector concatenation respectively. Each syntactic feature $x_i^{(j)}$ is a vector denoting probability distribution of a token over the corresponding feature labels (including being a one-hot vector), this is crucial because a token (especially subword-token) might have different labels depending on the context.

We train different MLPs and Embeddings from scratch for each alphabet $\alpha$ with no shared parameters across the (case-insensitive) 26 English alphabets. We train our model for binary classification via backpropagation over the standard Binary Cross Entropy loss across the predicted logits $\hat{y}_i$ and ground truth logits $y_i$.

As before, for each character we create a balanced dataset consisting of equal number of positive and negative examples, where each example is made up entirely of either English alphabets or whitespace. These are randomly divided into training and test split which keep words with same tokens with same lemmas in the same split.

For control task we randomly assign the syntactic features for each token. We set the batch size for runs with one-hot vectors as features to 128 and to 64 for others, the learning rate is tuned in $\{1e^{-5}, 3e^{-5}, 1e^{-4}, 3e^{-4}, 1e^{-3}, 3e^{-3}, 1e^{-2}\}$ for all the features over the metric of Averaged F1-Scores across the 26 English letters. The best learning rates for SpaCy, BERT-sentence, BERT-token, GPT-J and Control were found to be 1e-3, 1e-3, 3e-3, 1e-4, 1e-2. Using Adam Optimizer we train each of the 26 models for 5 epochs with betas of 0.9 & 0.999 and epsilon of 1e-8. Our implementation is done using PyTorch and Huggingface. Finally for the best hyperparameter, we perform 5 runs with different train/test splits and seeds. Our MLP model is 3-layered with SELU and Tanh activation and 0.1 Dropout before the last layer.

Tables 11 and 12 show the mean and variance of the results over the 4taggers and control task. We also show the performance over the best and worst performing letters.

**Appendix D Variability of Tokenization**

**D.1 Quantifying variability in the Pile Corpus**

To quantify the variability in the tokenization of frequent words in the kind of corpora used to train these models, we consider 1/6th of the publicly available Pile Corpus used to train GPT-J (250 GB of text). For our analysis we consider 500 frequent words of 8+ characters (as measured using Google Ngrams) since long words are more likely to be the source of variability.

For each target word, we first case-insensitively detect each of its occurrence in the sub-corpus. In order to also account for spelling errors, we used case-insensitive fuzzy search allowing matches of substring up to 1 Levenshtein distance away. Over these occurrences, we discard those where the substring is part of a bigger word, such as some ‘differentiation’ for the target word ‘different’ or if the fuzzy match has whitespaces.

Once we have such occurrences, we want to obtain the tokenization of the target word in the context. For this reason, we obtain the adjust the indices of the possibly-misspelt matched-substring for our target word till the nearest non-word, this allows for matches of [somethin’, somethin”, somethin’] all to be considered as the string ‘somethin’. We also account the factors that leads to differing tokenization, such as preceeding whitespaces.

Now, for each of the target words, we have a list of probable tokenization at most 1 Levenshtein distance away. Since two target words such as ‘projection’ and ‘protection’ could themselves be at 1 Levenshtein distance, these may act as pseudo matches for each other. So we consider only one of these two from our target list, leading to 466 word down from 500 words. Now, for each of these target words, we count the number of possible unique tokenizations.

For each of these 466 target words, we also obtain a list of words from the WordNet which are 1 Levenshtein distance away. We call this word list as the pseudo-match list. We also consider the number of tokenization for each target words, excluding their pseudo-match list as well as by excluding all those which are equally (or closer) to any word in pseudo-match list than the target word. We also compute the statistics of those with exact matches.

Table 13 shows these statistics for the target
words. On average, a target word is expected to have 213 different tokenization depending on the context. We observe that while one may expect the number of tokenization to go up with the number of characters in the target word, it doesn’t perfectly increase monotonically. This is because the number of occurrences of the target word, dictates the number of tokenization it will have, and there we see a consistent trend that the number of tokenization greatly increases with increasing occurrences. It is due to this reason, we expect this number to be even higher, when considering the entire Pile corpus, instead of the subset in our case.

We observe three factors contributing to surprisingly large number of tokenization. First, it is because of Case-Sensitive tokenization, which leads to up to 6 different tokenization for each of the target words. Second, its the context dependent tokenization, which increases the expected number of different tokenization to 12.91. Lastly, the remainder is contributed by the previous two combined with misspellings.

Our implementation is sped up using multiprocessing and fuzzy regex. For this we split the sub-corpus across multiple pieces. These runs takes about 3 days across 40 CPU Cores, 60 GB of RAM and less than 600GB hard disk space. Our experiment was only conducted on a portion of the Pile corpus, and the possible tokenizations for each target word is expected to increase with larger corpus size. We report the mean and standard deviation in the number of tokenizations a word has across the portion of the Pile corpus considered. These are also reported as a function of word length and its frequency of occurrence in the corpus.

Tables 13 and 14 shows these score. The ‘All matches’ field considers the unique tokenizations of all matched substrings including those at 1 (case and whitespace insensitive) Levenstein distance away. These word at 1 Levenstein distance could be either misspellings or a different English word (for example an occurrence of the word ‘projection’ could be a misspelling of either ‘pro- jection’ or ‘projection’ being at distance 1 from both). Such occurrences are removed and statistics recomputed for the column ‘Matches closer to pseudo’. The column ‘Exact contain’ considers only those occurrences, which contain the exact target word (case-insensitively) in the string ignoring whitespaces. Whereas the ‘Exact match’ does not consider the occurrences involving a preceeding whitespace.

Table 15 shows some examples for the variation in tokenization.

D.2 Algorithm for increasing tokenization variability

| Algorithm 1 | A simplified version of subword Tokenization with controllable variability |
|-------------|--------------------------------------------------------------------------------|
| Require:   | 0 <= ρ <= 1                                                                   |
| procedure  | YOUR FUNCTION(sentence)                                                        |
| tokens ← List() | words ← wordTokenize(sentences)                                               |
| for each w in words do |
| u ∼ Uniform[0, 1] if u < ρ then |
| V ← GPTJ.Vocab filter(V, λx.isAlphabetic(x)) Choices ← List() |
| for i in 1, 2 . . . (w.length() − 1) do |
| if w[i] ∈ V & w[i] ∈ V then |
| push(Choices, w[i], w[i]) end if |
| end for |
| if ¬ isEmpty(Choices) then |
| s ∼ Choices |
| tokens ← Merge(tokens, s) continue end if |
| end if |
| s ← GPTJ.Tokenize(w) tokens ← Merge(tokens, s) end for |
| end procedure |

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### Table 13: Tokenization Variance statistics - mean score.

| Measure                  | All Matches | Matches except pseudo | Matches closer pseudo | Exact contain | Exact match | Num Words |
|--------------------------|-------------|-----------------------|-----------------------|--------------|-------------|------------|
| Aggregate                | 95.72       | 94.49                 | 91.26                 | 17.71        | 2.97        |            |
| All Matches              | 232.90      | 229.70                | 213.74                | 17.91        | 5.97        | 466        |
| 7 Length words           | 297.50      | 271.00                | 232.50                | 22.00        | 6.5         | 2          |
| 8 Length words           | 332.29      | 325.68                | 288.07                | 25.00        | 7.89        | 28         |
| 9 Length words           | 231.48      | 227.78                | 206.95                | 16.94        | 5.93        | 190        |
| 10 Length words          | 225.51      | 222.58                | 209.53                | 17.97        | 5.87        | 127        |
| 11 Length words          | 213.28      | 211.02                | 202.97                | 17.88        | 5.85        | 61         |
| 12 Length words          | 224.14      | 223.54                | 218.64                | 18.25        | 5.79        | 28         |
| 13 Length words          | 218.14      | 217.00                | 214.76                | 16.57        | 5.19        | 21         |
| 14 Length words          | 238.33      | 238.33                | 238.33                | 16.67        | 5.00        | 9          |
| exp(12) occurrence       | 88.70       | 86.67                 | 82.11                 | 10.33        | 5.90        | 27         |
| exp(13) occurrence       | 155.78      | 153.87                | 146.55                | 13.61        | 5.15        | 74         |
| exp(14) occurrence       | 210.36      | 207.51                | 195.74                | 16.70        | 5.75        | 174        |
| exp(15) occurrence       | 278.88      | 275.00                | 251.69                | 19.91        | 5.96        | 139        |
| exp(16) occurrence       | 370.02      | 365.04                | 336.48                | 26.62        | 8.56        | 52         |

### Table 14: Variability across target words in Tokenization Variance statistics.

| String tokenization | String tokenization | String tokenization |
|---------------------|---------------------|---------------------|
| SIGNATURE           | "SIGNATURE", "ATURE"| "Playstation"       |
| SIGNATURE           | "SIGNATURE", "ATURE"| "PlayStation"       |
| SIGNATURE           | "SIGNATURE", "ATURE"| "PLAYSTATION"       |
| SIGNATURE           | "SIGNATURE", "ATURE"| "PERSONAL"          |
| SIGNATURE           | "SIGNATURE", "ATURE"| "PERSONAL"          |
| SIGNATURE           | "SIGNATURE", "ATURE"| "PERSONAL"          |
| SIGNATURE           | "SIGNATURE", "ATURE"| "PERSONAL"          |
| SIGNATURE           | "SIGNATURE", "ATURE"| "PERSONAL"          |

### Table 15: Some examples of variations in Tokenization for 3 frequent long words.