Abstract

Meaning is context-dependent, but many properties of language (should) remain the same even if we transform the context. For example, sentiment, entailment, or speaker properties should be the same in a translation and original of a text. We introduce language invariant properties: i.e., properties that should not change when we transform text, and how they can be used to quantitatively evaluate the robustness of transformation algorithms. We use translation and paraphrasing as transformation examples, but our findings apply more broadly to any transformation. Our results indicate that many NLP transformations change properties like author characteristics, i.e., make them sound more male. We believe that studying these properties will allow NLP to address both social factors and pragmatic aspects of language. We also release an application suite that can be used to evaluate the invariance of transformation applications.

1 Introduction

The meaning of a sentence is influenced by a host of factors, among them who says it and when: “That was a sick performance” changes meaning depending on whether a 16-year-old says it at a concert or a 76-year-old after the opera. However, there are several properties of language that do (or should) not change when we transform a text (i.e., change the surface form of it to another text, see also Section 2). If the text was written by a 25-year-old female it should not be perceived as written by an old man after we apply a paraphrasing algorithm. The same goes for other properties, like sentiment: A positive message like “good morning!” posted on a social media, should be perceived as a positive message, even when it is translated into another language. We refer to these properties that are unaffected by transformations as Language Invariant Properties (LIPs).

LIPs preserve the semantics and pragmatic components of language. I.e., these properties are not affected by transformations applied to the text. For example, we do not expect a summary to change the topic of a sentence.

Paraphrasing, summarization, style transfer, and machine translation are all NLP transformation tasks that we expect to respect the LIPs. If they do not, it is a strong indication that the system is picking up on spurious signals, and needs to be recalibrated. For example, machine translation should not change speaker demographics or sentiment, paraphrasing should not change entailment or topic.

However, an important question is, what happens if a transformation does violate invariants? Violating invariants is similar to breaking the cooperative principle (Grice, 1975): if we do it deliberately, we might want to achieve an effect. For example, Reddy and Knight (2016) showed how words can be replaced to obfuscate author gender and thereby protect their identity. Style transfer can therefore be construed as a deliberate violation of LIPs. In most cases, though, violating a LIP will result in an unintended outcome or interpretation of the transformed text: for example, violating LIPs on sentiment will generate misunderstanding in the interpretation of messages. Any such violation might be a signal that models are not ready for production (Bianchi and Hovy, 2021).

We know that cultural differences can make it more difficult to preserve LIPs (Hovy and Yang, 2021): it might not be possible to effectively trans-
late a positive message into a language that does not share the same appreciation/valence for the same things. However, this is a more general limitation of machine translation. The speaker’s intentions are to keep the message consistent - in term of LIPs - even when translated.

We define the concept of LIPs, but also integrate insights from Hovy et al. (2020), defining an initial benchmark to study LIPs in two of the most well-known transformation tasks: machine translation and paraphrasing. We apply those principles more broadly to transformations in NLP as a whole.

Contributions. We introduce the concept of LIPs as those properties of language that should not change during a transformation. We propose an evaluation methodology for LIPs and release a benchmark that can be used to test how well translation systems can preserve LIPs for different languages.

2 Language Invariant Properties

To use the concept of LIPs, we first need to make clear what we mean by it. We formally define LIPs and transformations below.

Assume the existence of a set $S$ of all the possible utterable sentences. Let’s define $A$ and $B$ as subsets of $S$. These can be in the same or different languages. Now, let’s define a mapping function

$$t : A \rightarrow B$$

i.e., $t(\cdot)$ is a transformation that changes the surface form of the text $A$ into $B$.

A language property $p$ is a function that maps elements of $S$ to a set $P$ of property values. $p$ is invariant if and only if

$$p(a) = p(t(a)) = p(b)$$

where $a \in A$, $b \in B$, and $t(a) = b$. I.e., if applying $p(\cdot)$ to both an utterance and its transformation still maps to the same property. We do not provide an exhaustive list of these properties, but suggest to include at least meaning, topic, sentiment, speaker demographics, and logical entailment.

LIPs are thus based on the concept of transformations in text. Machine translation is a salient example of a transformation, and probably the prime example of a task for which LIPs are important. MT can be viewed as a transformation between two languages where the main fundamental LIP that should not be broken is meaning.

However, LIPs are not restricted to MT, but have broader applicability, e.g., in style transfer. In that case, though, some context has to be defined. When applying a formal to polite transfer, this function is by definition not invariant anymore. Nonetheless, many other properties should not be influenced by this transformation. Finally, for paraphrasing, we have only one language, but we have the additional constraint that $t(a) \neq a$. For summarization, the constraint instead is that $\text{len}(t(a)) < \text{len}(a)$.

LIPs are also what make some tasks in language more difficult than others: for example, data augmentation (Feng et al., 2021) cannot be as easily implemented in text data as in image processing, since even subtle changes to a sentence can affect meaning and style. Changing the slant or skew of a photo will still show the same object, but e.g., word replacement easily breaks LIPs, since the final meaning of the final sentence and the perceived characteristics can differ. Even replacing a word with one that is similar can affect LIPs. For example, consider machine translation with a parallel
corpus: “the dogs are running” can be paired with
the translation “I cani stanno correndo” in Italian.
If we were to do augmentation, replacing dogs
with its hyperonym “animals” does not corrupt the
overall meaning, as the new English sentence still
entails all that is entailed by the old one. However,
the Italian example is no longer a correct transla-
tion of the new sentence, since “cani” is not the
word for animals.

LIPs are also part of the communication between
speakers. The information encoded in a sentence
uttered by one speaker contains LIPs that are im-
portant for efficient communication, as misunder-
standing a positive comment as a negative one can
create issues between communication partners.

Note that we are not interested in evaluating the
quality of the transformation (e.g., the translation or
paraphrase). There are many different metrics and
evaluation benchmarks for that (BLEU, ROUGE,
etc.: Papineni et al., 2002; Lin, 2004). Our analysis
concerns another aspect of communication.

The general ideas behind LIPs shares some
notions with the Beyond Accuracy Checklist by
Ribeiro et al. (2020). However, LIPs evaluate how
well fundamental properties of discourse are pre-
served in a transformation, the CheckList is made
to guide users in a fine-grained analysis of the
model performance to better understand bugs in the
applications with the use of templates. As we will
show later, LIPs can be quickly tested to any new
annotated dataset. Some of the checklist’ tests, like
Replace neutral words with other neutral words
can be seen as LIPs. Nonetheless, we think the two
frameworks are complementary.

3 Evaluating Transformation Invariance

For ease of reading, we will use translation as an
example of a transformation in the following. How-
ever, the concept can be applied to any of the trans-
formations we mentioned above.

We start with a set of original texts \( O \) to translate
and a translation model from the source language
of \( O \) to a target language. To test the transfor-
mation wrt a LIP, \( O \) should be annotated with that
language property of interest. We also need a clas-
sifier for the LIP. For example, a LIP classifier
could be a gender classifier that given an input text
returns the inferred gender of the speaker. Here,
we need one cross-lingual classifier, or two classi-
fiers, one in the source and one in the target lan-
guage. For all other transformations, which stay
in the same language, we only need one classifier.

(Paraphrasing or summarization can be viewed as
a transformation from English to English).

After we translate the test set, we can run the
classifier on the \( O \) data, to get its predictions (\( PO \)).
We then run the classifier on the transformed data,
generating the predictions on the transformed data
(\( PT \)).

We can then compare the difference between
the distribution of the LIP in the original data and
either prediction. I.e., we compare the differences
of \( O - PO \) to \( O - PT \) to understand the effect of
the transformations.

Note that we are not interested in the actual per-
f ormance of the classifier, but in the difference in
performance on the two data sets. We observe two
possible phenomena:

- If there is a classifier bias, both the predic-
tions based on the original language and the
predictions based on the translations should
be skewed in the same direction wrt the dis-
tribution in \( O \). E.g., for gender classification,
both classifiers predict a higher rate of male
authors in the original and in the translated
text.

- Instead, if there is a transformation bias, then
the distribution of the translated predictions
should be skewed in a different direction than
the one based on the original language. E.g.,
the gender distribution in the original lan-
guage should be less skewed than the gender
ratio in the translation.

As we will see in the next Section, it is possible
to use divergence metrics (like the KL divergence)
to quantify the difference between the classifiers.
To reduce one of the possible sources of bias, the
classifier should be trained with data that comes
from a similar distribution to the one used at test
time, ideally from the same collection.

4 Benchmark Tool

We release an extensible benchmark tool\(^3\) that can
be used to quickly assess a model’s capability to
handle LIPs.

4.1 Datasets

Here, we evaluate machine translation and para-
phrasing as tasks. Our first release of this bench-
mark tool contains the datasets from Hovy et al.

\(^3\)https://github.com/MilaNLP/proc/language-invariant-properties
The benchmark has been designed to provide a high-level API that can be integrated in any transformation pipeline. Users can access the dataset text, transform, and score it.

Figure 2: The benchmark has been designed to provide a high-level API that can be integrated in any transformation pipeline. Users can access the dataset text, transform, and score it.

The benchmark we provide can be easily extended with new datasets encoding other LIPs.

**TrustPilot** The dataset is a subset of the one originally presented by Hovy et al. (2015) and contains TrustPilot reviews in English, Italian, German, French, and Dutch with demographic information about the user age and gender. Training data for the different languages consists of 5,000 samples (2,500 for the male and 2,500 for the female genders). More information can be found in the original work Hovy et al. (2020). The dataset can be used to evaluate the LIPs AUTHOR-GENDER and AUTHOR-AGE.

**HatEval** We use the data from HatEval (Basile et al., 2019) considering only English tweets. We take the training (9,000 examples) and test set (3,000 examples). Each tweet comes with a value that indicates if the tweet contains hate speech. The dataset can be used to evaluate the LIP HATEFULNESS.

**Affects in Tweets** We also use the Affect in Tweets dataset (AiT) (Mohammad et al., 2018), which contains tweets annotated with emotions. We will use this dataset to test how sentiment and emotions are affected by translation. We do not expect much variation in the distribution, since both emotion and sentiment should be efficiently translated; this is exactly what we would like our evaluation framework to show.

To reduce the number of possible classes to predict we only kept emotions in the set \{fear, joy, anger, sadness\} to allow for future comparisons with other datasets. This subset is also easy to map to other labels to create a sentiment analysis task: we map joy to positive and the other emotions to negative following Bianchi et al. (2021). The data we collected comes in English (train: 4,257, test: 2,149) and Spanish (train: 2,366, test: 1,908). The dataset can be used to evaluate the LIP SENTIMENT.

### 4.2 Classifiers

As default classifier we use a Logistic Regression models with L2 regularization over 2-6 TF-IDF character-grams like Hovy et al. (2020). We also provide the use of embedding models from SBERT (Reimers and Gurevych, 2019) to generate representations of documents that we can then classify with logistic regression (see Appendix). The two classification methods are referred to as TF (TF-IDF) and SE (Sentence Embeddings). The framework supports the use of any custom classifiers.

### 4.3 Scoring

Standard metrics for classification evaluation can be used to assess how much LIPs are preserved during a transformation. Following Hovy et al. (2020) we use the KL divergence to compute the distance - in terms of the distribution divergence - between the two predicted distributions. The benchmark also outputs the $X^2$ test to assess if there is a significant difference in the predicted distributions. It is also possible to look at the plots of the distribution to understand the effects of the transformations (see following examples in Figures 3, 4 and 5).

## 5 Evaluation

We evaluate four tasks, i.e., combinations of transformations (translation and paraphrasing) and LIPs (gender, sentiment, and hatefulness). The combination is determined by the availability of the particular property in the respective dataset.

### 5.1 TrustPilot Translation - LIP: AUTHOR-GENDER

We use the TrustPilot dataset to study the author-gender LIP during translation. We use the google translated documents provided by the authors. We are essentially recomputing the results that appear
in the work by Hovy et al. (2020). As shown in Table 1, our experiments confirm the one in the paper: it is easy to see that the translations from both Italian and German are more likely to be predicted as male.

### 5.2 AiT Translation - LIP: SENTIMENT

We use the AiT dataset to test the sentiment LIP during translation. We translate the tweets from Spanish to English using DeepL. As shown in Figure 3, sentiment is a property that seems to be easily kept during translations. This is expected, as sentiment is a fundamental part of the meaning of a sentence and has to be translated accordingly.

### 5.3 TrustPilot Paraphrasing - LIP: AUTHOR-GENDER

We use the TrustPilot dataset to test the author-gender LIP in the context of paraphrasing. When we apply paraphrasing on the data, the classifier on the transformed data predicts more samples as male, as shown by the Figure 4 that plots the distribution ($KL_{O,PT} = 0.018$, difference significant for $X^2$ with $p < 0.01$).

### 5.4 HatEval Paraphrasing - LIP: HATEFULNESS

We use the HatEval data to study the hatefulness LIP after paraphrasing. Figure 5 shows the change in the predicted distribution: while the classifier predicted a high amount of hateful tweets in $PO$ (a problem due to the differences between the training and the test in HatEval (Basile et al., 2019; Nozza, 2021)), this number is drastically reduced in $PT$, demonstrating that paraphrasing reduce hatefulness.

As an example of paraphrased text, *Savage Indians living up to their reputation* has been transformed to *Indians are living up to their reputation*. While the message stills internalize some hatefulness, the removal of the term *Savage* has reduced its strength. It is important to remark that we are not currently evaluating the quality of the transformation, as this is another task: the results we obtain are in part due to the paraphrasing tool we used, but they still indicate a limit in the model capabilities.

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5. https://huggingface.co/tuner007/pegasus_paraphrase
### 6 Limitations

While LIPs make an interesting theoretical concept, they might not always be so easy to generalize to some tasks: For example, translating from Spanish to Japanese has to take account of the cultural differences of the two countries and it might not be possible to reduce these to a set of LIPs.

The tool we implemented comes with some limitations. We cannot completely removed the learned bias in the classifiers and we always assume that when there are two classifiers, these two perform reliably well on both languages so that we can compare the output. The same goes for the paraphrasing: we assume that the LIP classifier perform equally well on both the original and the transformed text.

### 7 Conclusion

This paper introduces the concept of Language Invariant Properties, properties in language that should not change during transformations. We believe the study of LIPs can improve the performance of different NLP tasks, like machine translation and paraphrasing. To provide better support in this direction we release a benchmark that can help researchers and practitioners understand how well their models handle LIPs.

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A Models in the Experiments

A.1 TrustPilot Paraphrase

We use the same classifier for the original and the transformed text. We generate the representations with SBERT. The model used is paraphrase-distilroberta-base-v2.6

As paraphrase model, we use a fine-tuned Pegasus (Zhang et al., 2020) model, pegasus paraphrase,7 that at the time of writing is one of the most downloaded on the HuggingFace Hub.

A.2 AiT Translation

We translated the tweets using the DeepL APIs.8 As classifiers we use the cross-lingual model for both languages, each language has its language-specific classifier. The cross-lingual sentence embedding method used is paraphrase-multilingual-mpnet-base-v2, from the SBERT package.

A.3 TrustPilot Translation

As translation we use the already translated sentences from the TrustPilot dataset provided by Hovy et al. (2020). We use both the TF-IDF based and the cross-lingual classifier, as shown in Table 1, each language has its own language-specific classifier. The cross-lingual sentence embedding method used is paraphrase-multilingual-mpnet-base-v2, from the SBERT package.

A.4 HatEval Paraphrasing

We use the same classifier for the original and the transformed text. We generate the representations with SBERT. Users are replaced with @user, hashtags are removed. The model used is paraphrase-distilroberta-base-v2.

As paraphrase model, we use a fine-tuned Pegasus (Zhang et al., 2020) model, pegasus paraphrase, that at the time of writing is one of the most downloaded on the HuggingFace Hub.

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6https://sbert.net
7https://huggingface.co/tuner007/pegasus_paraphrase
8https://deepl.com/