# Common Ground, Diverse Roots: The Difficulty of Classifying Spanish Variants

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## Abstract

Variations in languages across geographic regions or cultures are crucial to address to avoid biases in NLP systems designed for culturally sensitive tasks, such as hate speech detection or dialog with conversational agents. In languages like Spanish, where variants can significantly overlap, many examples can be valid across multiple dialects or variants, which we refer to as common examples. Ignoring these examples may cause misclassifications, reducing model accuracy and fairness. Therefore, accounting for these common examples is essential to improve the robustness and representativeness of NLP systems trained on such data. In this work, we address this problem in the context of Spanish variants. We use training dynamics to automatically detect common examples or errors in existing Spanish datasets. We demonstrate the efficacy of using predicted label confidence for our Data Maps implementation for the identification of hard-to-classify examples, especially common examples, enhancing model performance in variant identification tasks. Additionally, we introduce a Cuban Spanish Variant Identification dataset with common examples annotations developed to facilitate more accurate detection of Cuban and Caribbean Spanish variants. To our knowledge, this is the first dataset focused on identifying the Cuban, or any other Caribbean, Spanish variant.

## 1 Introduction

Language reflects culture and identity while also capturing subtle variations that shape communication. In Natural Language Processing (NLP), it is crucial to account for these nuances, especially in language variant identification, where small shifts in meaning, often tied to cultural interpretations, can impact sensitive tasks like hate speech detection. Expressions that may be benign in one dialect can be offensive in another, making thus accurate variant identification essential for preventing misclassifications and ensuring culturally appropriate responses (Nozza, 2021; Hershcovich et al., 2022). In such tasks, cross-lingual models often struggle

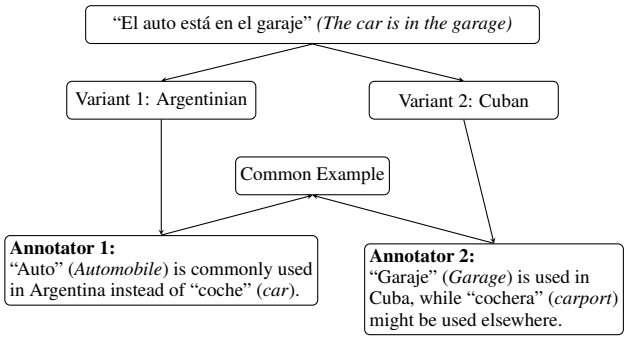



Figure 1: Common Example Identification in Language Variant Classification

with these subtle cultural and linguistic distinctions, as the same formulation may carry vastly different meanings across dialects. Language-specific models tend to perform better in such cases, as they are more sensitive to regional variations (Nozza, 2021; Vaidya et al., 2024; Arango et al., 2021; Montariol et al., 2022; Castillo-lópez et al., 2023). However, distinguishing between closely related languages, dialects, and regional varieties of the same language is a key and difficult task in language identification (Tiedemann and Ljubešić, 2012; Lui and Cook, 2013; Zampieri and Nakov, 2021). Adding to this complexity is the issue of 'common examples'—valid phrases across multiple dialects. Overlooking these examples can result in biased classifications, especially in languages like Spanish, where dialect overlap is frequent. Despite this, many current datasets treat language variant identification as a single-label classification task, which overlooks this crucial aspect (Zampieri et al., 2024). Current datasets for language variant identification often rely on manual annotations or automated methods such as geographic information (Zampieri et al., 2019; Abdul-Mageed et al., 2020, 2022; Aepli et al., 2022) or keyword-based clas-

sification (Althobaiti, 2022). However, both approaches have limitations, and manually checking large datasets for common examples is challenging and costly (Keleg and Magdy, 2023; Bernier-colborne et al., 2023). Datamaps based on training dynamics (Swayamdipta et al., 2020; Weber-Genzel et al., 2024), which track how the model's confidence changes across epochs, have been used successfully to detect annotation errors and human label variation. These methods highlight which examples are consistently easy or difficult for the model, with hard examples often pointing to ambiguity or errors. We propose using training dynamics to detect common examples in language variant identification tasks. These are expected to be among the hard examples the model struggles with during training. By tracking the model's confidence in its predicted labels over multiple training epochs, rather than using gold labels, we aim to detect ambiguous instances that are hard for the model to classify consistently. Our research addresses the following questions:

- **RQ1:** Can training dynamics help detect common examples that are hard for the model to classify during the training?
- **RQ2:** Can we use the model's confidence over predicted labels to detect common examples?
- **RQ3:** Can this approach work effectively across different domains, such as news articles and user-generated content?

To investigate these questions, we use two datasets: the Spanish subset of DSL-TL dataset (Zampieri et al., 2024), which contains texts extracted from news articles, and a new dataset of Cuban Spanish variants we collected from Twitter. We adapt the Datamaps technique by changing how confidence and variability are calculated, allowing us to identify common examples. Our results demonstrate the efficiency of this approach in detecting common examples across both datasets.

Our main contributions are:

1. We propose a modified Datamaps model that calculates confidence and variability based on the predicted label's probability, providing a more accurate reflection of model uncertainty. Our model can help accelerate the re-annotation of existing datasets.
2. Using both frequency-based methods and SHAP analysis (Lundberg and Lee, 2017), we provide a thorough error analysis that demonstrate the usefulness of our approach to capture annotation errors and shows how the model's predictions are topic dependent.
3. We present and publicly share a novel Cuban Spanish variant identification dataset, consisting of 1,762 manually annotated tweets by three native speakers, with labels assigned based on agreement and covering Cuban, non-Cuban variants, and common examples.

## 2 Related Work

**Common Examples in Variant Annotation.** The challenge of handling common examples instances that can be valid across multiple language variants has been a recurring issue in language variant identification. Traditional single-label classification often struggles to assign unique labels to common examples.(Althobaiti, 2020; Bernier-colborne et al., 2023). Addressing this challenge, Zampieri et al. (2024) introduced a third class specifically for common instances in their DSL-TL dataset for language variety identification. This dataset allowed the exploration of these ambiguous cases' impact on model performance. The authors found that models had difficulty distinguishing between common and dialect-specific examples. Then, their results served as a baseline for the DSL-TL shared task at VarDial 2023 (Aepli et al., 2023). In the scope of this shared task, Vaidya and Kane (2023) introduced a two-stage multilingual dialect detection system. Their approach first identifies the macro-language, followed by applying dialect-specific models to refine the classification. While this system performed well overall, it struggled with the common examples class, where it frequently misclassified examples due to the lack of clear dialect-specific markers. The Spanish language, with its rich array of variants, provides a particularly challenging landscape for variant identification due to the high similarity between variants. Zampieri et al. (2024) noted that the prevalence of common examples in Spanish is especially high. Given the significant lexical and syntactical overlap among Spanish variants, sentences that can belong to more than one variant are frequent, making traditional classification approaches less reliable. The misclassification of these common instances not only introduces noise into the datasets but also impacts the overall performance of models, as evidenced by the poor handling of Argentine examples in Vaidya and Kane (2023).

**Multi-class Approaches for Variant Identification.** In light of these challenges impacting many

different languages, several works have proposed moving away from single-label classification towards multi-class or multi-label approaches for variant identification. For instance, Keleg and Magdy (2023) demonstrated that many sentences could validly belong to multiple Arabic dialects, arguing for including multiple labels per instance. They introduced the Expected Maximal Accuracy (EMA) metric to measure the upper-bound accuracy in scenarios where common instances occur frequently. Their results indicated that the majority of false positives in traditional single-label classifiers were, in fact, not errors but cases where multiple dialects could be correct. Bernier-colborne et al. (2023) took this further by employing similarity metrics to identify duplicate or nearly duplicate examples and assigning multiple labels to ambiguous sentences. Their work, focusing on French variants, showed that this multi-class approach significantly improved F1-macro scores for ambiguous examples. They argued that applying a multi-class framework can improve the accuracy of variant identification and better handle the inherent ambiguity found in multilingual datasets.

## 3 Task Definition: Automatic Common Examples Detection

Our main task is to identify common examples across similar language variants. Our proposed pipeline can be separated into two main stages:

- Fine-tune a Transformer-based model on the Variant Identification datasets for single-label classification of variants (binary).
- Assign a score to each example using a scorer model, expecting higher values for common examples, and rank them with the highest scores at the top.

### 3.1 Scorer Models

**DataMaps** Swayamdipta et al. (2020) proposed DataMaps (DM) using Training Dynamics, which is the behavior of a model as training progresses, for detecting annotation errors in datasets. Their approach focused on tracking the confidence and variability on the gold label during training. Specifically, examples consistently showing low confidence for this label across epochs were flagged as potential annotation errors or ambiguous cases. This technique has also been adapted for identifying human label variation, where examples can legitimately belong to more than one category (Weber-Genzel et al., 2024). We use this technique to identify common examples for the Variant Identification task.

**Datamaps using predicted label probability** We adapt the Datamaps metrics to our use case. Unlike Swayamdipta et al. (2020), who focus on the gold labels, and Weber-Genzel et al. (2024), who prioritize re-annotating erroneous labels, our goal is to detect instances that the model struggles to classify consistently. Therefore, we calculate confidence and variability differently: rather than focusing on the correctness of assigned labels or identifying annotation errors, we calculate these metrics based on the maximum predicted probability for each instance at each epoch, aiming to detect instances that exhibit inconsistent predictions or low confidence and, therefore, could belong to both classes or an unobserved third class. For common examples, which can be associated with more than one label, it would be more natural to describe the uncertainty in terms of the model's confidence in its predictions. The *confidence* is defined as:

$$DM_{mean-pred} = -\frac{1}{E}\sum_{e=1}^{E} max_j(p_{i,j,e}) \quad (1)$$

where $p_{i,j,e}$ is the probability assigned to the $i$'th instance for the label $j$ in epoch $e$. Then, the lowest confidences correspond to a higher score because of the negative sign. The idea is that examples with small probabilities associated with the predicted label across the epochs are likely challenging examples.

The *variability* is defined as:

$$DM_{std-pred} = \sqrt{\frac{1}{E}(\sum_{e=1}^{E} max_j(p_{i,j,e}) + DM_{mean-pred})^2} \quad (2)$$

High *variability* indicates that the model's confidence changes significantly across epochs, suggesting the model is uncertain about the instance. This can point to an instance that is hard to classify or potentially common.

**Random baseline** We use a random model as a scorer, which assigns uniformly random scores between 0 and 1 to each example as a baseline.

**Language Model** For the Variant Identification module we use the model BETO, the monolingual Spanish BERT model version (Canete et al.,

2020) for our experiments; it has proven effective in several downstream tasks for this language. This model was trained on the entire Wikipedia and all the Spanish data from OPUS project (Tiedemann, 2012). In the case of Spanish Wikipedia, by 2017, around 39.2% of edits came from Spain (Spanish Wikipedia, 2021), which can negatively impact the model performance in variants not from Spain.

**Evaluation** The first metric considered for evaluation is the Average Precision Score in the Common Examples Identification Task. In addition, we evaluate precision and recall by considering the top N instances, ranked by their score values, with N ranging from 10 to the size of each dataset.

## 4 Datasets

In this section, we describe the datasets used for our analysis. We use an existing dataset DSL-TL and propose a new dataset CUBANSPVARIANT focused on the Cuban Spanish variant.

### 4.1 DSL-TL

The Discriminating Similar Language - True Labels (DSL-TL) dataset (Zampieri et al., 2024) was employed in a shared task at the VarDial 2023 workshop[1]. This dataset contains examples from Portuguese, Spanish, and English variants, but our focus is solely on the Spanish subset. The Spanish subset is derived from the DSLCC dataset (Tan et al., 2014) and includes sentences extracted from various Argentinian and Spanish newspapers, with each example annotated based on the country associated with the news source. However, annotating the examples with a single label proved difficult, even for human annotators (Goutte et al., 2016). Specifically, Spanish annotators achieved an average accuracy of only 54.90%. To address these challenges, Zampieri et al. (2024) randomly sampled the Spanish, Portuguese, and English subsets and conducted a new round of human annotations. In addition to the original binary labels, a third label—*both or neither*—was introduced. This additional label was assigned when annotators could not identify distinguishing variant features. For our experiments with the DSL-TL dataset, we use the newly introduced labels from the DSL-TL dataset and the original labels from the DSL-2014 corpus. It allowed us to simulate a scenario where new annotations would be unavailable. We only use the training set to analyze the training dynamics.

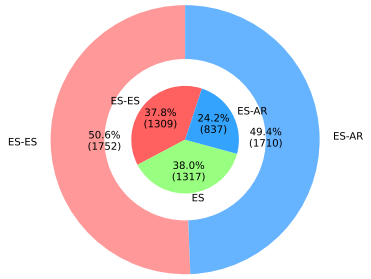
[1] VarDial 2023 website.

### 4.2 CUBANSPVARIANT

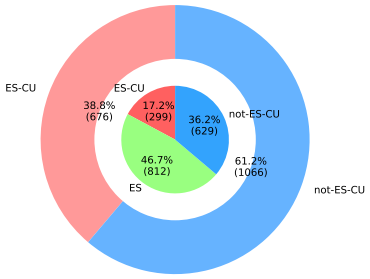
To our knowledge, the dataset is the first dataset for Cuban or any Caribbean Spanish variant identification. The dataset contains manually annotated tweets with variant information. We collected the data from the publicly available archive *The Twitter Stream Grab* in the website archive.org. We worked particularly with data from July 2021 [2].

**Data Annotation.** We randomly sampled 10000 tweets from July 11th and July 12th. Among those, we finally annotated 1762 examples. We considered this time frame because of the high Twitter activity in Cuba after July 11th protest in 2021 with trending hashtags such as *#SOSCuba* or *#SOSMatanzas* [3]. Each tweet was annotated across five columns: *cuban_variant*, *not_cuban_variant*, *specific_variant*, *not_able_to_identify*, and *irrelevant*. Annotators marked *cuban_variant* if the tweet belonged to the Cuban Spanish variant and

[2] Link to available data for July 2021.
[3] New York Times (July 11th, 2O21).




(a) DSL-TL dataset distribution.




(b) CUBANSPVARIANT dataset distribution.

Figure 2: Datasets distributions.

*not_cuban_variant* if it did not (cf. Section B). In case of identifying a different Spanish variant (e.g., from Spain or Chile), they were asked to annotate it in the *specific_variant* column for future work. When uncertain about the variant, they marked *not_able_to_identify*. Tweets deemed noisy or non-Spanish were marked as *irrelevant*.

We focused on three labels for analysis: *ES-CU* (Cuban variant), *not-ES-CU* (non-Cuban), and *ES* (common examples). Tweets with *cuban_variant* marked True were labeled *ES-CU*, those with *not_cuban_variant* marked True were labeled *not-ES-CU*, and tweets marked only as *not_able_to_identify* were labeled *ES*, aligning with the DSL-TL dataset. Three volunteers, native Cuban Spanish speakers with a Master's education in Cuba performed the annotations. Their familiarity with other Spanish variants helped them to recognize common examples. Labels were assigned when at least two annotators agreed, and tweets marked as irrelevant by any annotator were discarded. Full agreement was reached for 984 examples (55.8%), partial agreement for 776 (43.5%), with disagreement in just 12 cases (0.7%). We use the full dataset for training dynamics analysis. In this case, we only have the annotations with the common examples information (i.e. not single label approach). Then, to simulate a real-world scenario with single labels, we randomly assigned each common example a label of either *ES-CU* or *not-ES-CU*. Figure 2b shows the final dataset distribution. The internal circle represents the original distribution (cf. Table 2 for a lexical properties overview).

## 5 Results

### 5.1 Variant Identification

We investigate the learning behavior of BETO-based Variant Identification model by analyzing the F1 scores across both datasets. Figure 3 presents the F1-score evaluation for Language Variant Classification over 10 training epochs, with separate curves for common examples and the rest of the data in both datasets. As shown in the figure, the performance gap between common and non-common examples is substantial during the early stages of training. Furthermore, the error bars indicate greater variability in the F1-scores for common examples than the rest. This gap is particularly pronounced in the CUBANSPVARIANT dataset, which exhibits lower F1 scores, likely due to the additional challenges of social media content, unlike DSL-TL, which contains sentences from newspaper articles. These observations suggest that the model finds it more challenging to learn common examples, supporting the idea that their characteristics can be identified through training dynamics.

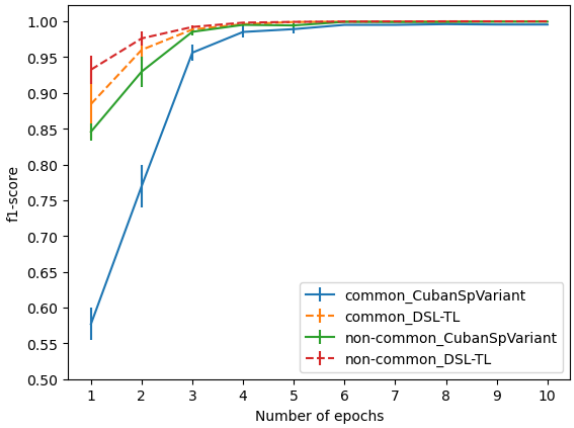



Figure 3: F1-score during training for common and non-common examples on both datasets.

### 5.2 Common Examples Identification

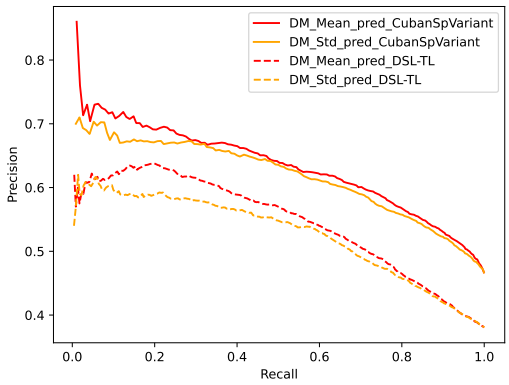



Figure 4: Precision versus recall curve

We present in Table 1 the results for both the DSL-TL and CUBANSPVARIANT datasets, comparing $DM_{\text{mean-pred}}$, $DM_{\text{std-pred}}$ and the random baseline. Across both datasets, the two Datamaps models significantly outperform the baseline, indicating that both capture relevant information about common examples. In addition, $DM_{\text{mean-pred}}$, which leverages the confidence in predicted labels, consistently outperforms $DM_{\text{std-pred}}$. This suggests that the model's average confidence offers a more reliable signal for identifying common examples, while the variability-based approach ($DM_{\text{std-pred}}$)

| Model | APS | Prec-500 | Recall-500 | Prec-1000 | Recall-1000 |
|---|---|---|---|---|---|
| | | | DSL-TL | | |
| Random | 39.45 ± 2.54 | 38.71 ± 1.49 | 14.98 ± 0.57 | 37.80 ± 1.16 | 28.99 ± 0.89 |
| $DM_{mean-pred}$ | **54.75 ± 1.8** | **62.78 ± 2.47** | **24.31 ± 0.95** | **57.76 ± 1.58** | **44.29 ± 1.21** |
| $DM_{std-pred}$ | 52.88 ± 3.00 | 58.70 ± 3.05 | 22.73 ± 1.18 | 56.03 ± 2.59 | 42.97 ± 1.98 |
| | | | CUBANSPVARIANT | | |
| Random | 46.42 ± 1.20 | 46.39 ± 2.32 | 29.10 ± 1.46 | 46.83 ± 0.52 | 58.17 ± 0.65 |
| $DM_{mean-pred}$ | **63.51 ± 2.56** | **66.19 ± 3.43** | **41.52 ± 2.15** | **59.16 ± 1.25** | **73.50 ± 1.55** |
| $DM_{std-pred}$ | 61.97 ± 2.60 | 64.86 ± 3.59 | 40.68 ± 2.25 | 58.15 ± 1.07 | 72.25 ± 1.33 |

Table 1: Evaluation metrics for Automatic Common Examples on DSL-TL and CUBANSPVARIANT datasets. We present the Average Precision Score, equivalent to the area under the precision-recall curve, and the precision and recall for Top-500 and Top-1000 instances. All the metrics are expressed in percentages.

tracks changes that don't always correspond with common examples. We observe that the difference in performance between the two datasets follows a similar pattern across all models, including the random baselines. This is likely due to the proportion of common examples in each dataset. In DSL-TL, where 38% of the examples are common, the random baseline precision is close to 38%. Similarly, in CUBANSPVARIANT, with 46% common examples, the baseline precision is near 46%. This suggests that the metrics' ranges are closely tied to each dataset's distribution of common examples.

Figure 4 shows both datasets' precision versus recall curves. In both cases, precision remains relatively stable in the early ranking stages and begins to converge toward the common examples' proportion as recall increases. The performance difference between $DM_{\text{mean-pred}}$ and $DM_{\text{std-pred}}$ is more pronounced for smaller values of N, particularly in precision. However, the recall curves show a steeper slope at earlier ranking stages, which gradually decreases as N increases, consistent with expected behavior.

Figure 6 highlights that in the DSL-TL dataset, which contains clean, edited content unlike our Twitter-based Cuban dataset, $DM_{\text{mean-pred}}$ identifies common examples early in the ranking. This is likely because we had access to the original labels for common examples in this dataset, reducing noise. Furthermore, the clear class boundaries distinguishing Spanish variants from Spain and Argentina likely contributed to the model's more stable performance, while $DM_{\text{std-pred}}$ is less effective in this context. In Figure 5, we observe that for the CUBANSPVARIANT dataset, which contains more dynamic and informal language from user-generated content, the performance gap between $DM_{\text{mean-pred}}$ and $DM_{\text{std-pred}}$ becomes smaller. This indicates that variability has a more significant impact on identifying common examples in user-generated content. In this dataset, common examples were identified in the first round and randomly assigned to Cuban or non-Cuban classes, increasing ambiguity. It is worth noting that, beyond the differences in dataset nature (newswire text VS Twitter user-generated content), the collection pe-

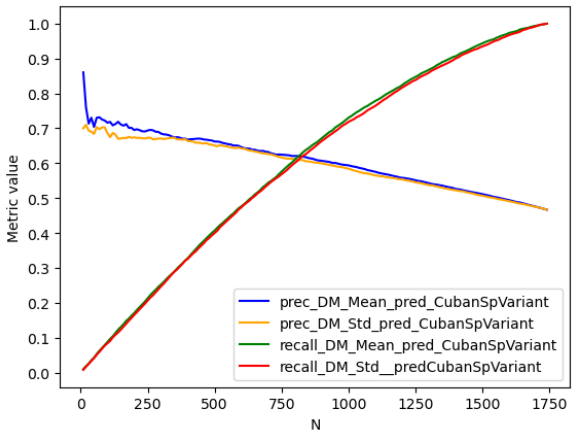



Figure 5: Precision and Recall versus Top-N instances CUBANSPVARIANT dataset

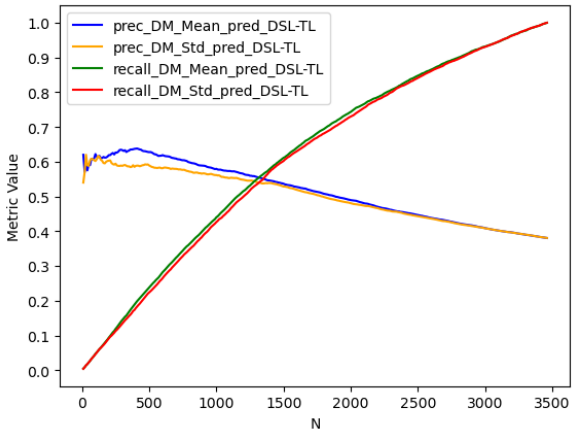



Figure 6: Precision and Recall versus Top-N instances DSL-TL dataset

riod dates vary over six years between both datasets, likely affecting model performance since languages evolve and are shaped by social dynamics. Furthermore, the Cuban dataset includes tweets from July 11th and 12th, during large protests in Cuba that were trending among Spanish-speaking countries. This may introduce biases into the dataset and influence the variant identification.

## 6 Error Analysis

To better understand our models' performance, we analyzed the errors for each dataset by counting the most frequent words in the Top-500 non-common instances predicted by the $DM_{mean-pred}$ model (prediction errors). After removing stopwords and special tokens, we found that in the CUBANSPVARIANT dataset, the most frequent words were *Cuba* and *SOSCuba*, directly tied to the Cuban variant in this context. In contrast, the DSL-TL dataset showed common words like *ha*, *pero*, *fue*, and *también*, which do not indicate a specific variant. The topic bias in the Cuban dataset may influence the model's predictions, mainly when examples contain variant-specific keywords. This also explains why $DM_{std-pred}$ performs better for CUBANSPVARIANT, as these keywords in both classes make variability more significant than in DSL-TL.

In the CUBANSPVARIANT dataset, Figure 7 shows that about 67% of the Top-500 non-common examples and 54% of the Top-1000 non-common examples contained the word *Cuba*, suggesting a strong influence on model behavior, given that only 33% of the total examples contain this word. Additionally, we found that 63.31% of the Top-500 errors in CUBANSPVARIANT were cases where only two annotators agreed on the label, and for the Top-1000, this number was 57%. Across all non-common instances, full agreement (three annotators) occurred in 57% of cases, indicating a clear link between annotation difficulty and model errors as shown in Figure 8.

Another key point is understanding why the model fails to retrieve certain common examples. We focus on the last two common examples in the ranking for each dataset, using SHapley Additive exPlanations (SHAP) (Lundberg and Lee, 2017) to analyze the model's behavior. SHAP is based on Game Theory and assigns importance scores to features, showing how much each feature influences the model's prediction. Figure 9a presents the SHAP scores for the last two common examples

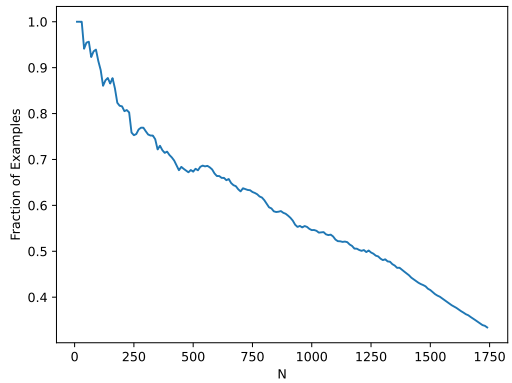



Figure 7: Fraction of error instances containing the word *Cuba* in Top-N instances using $DM_mean$ score metric.

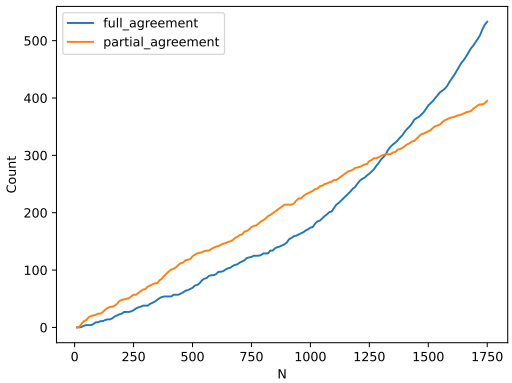
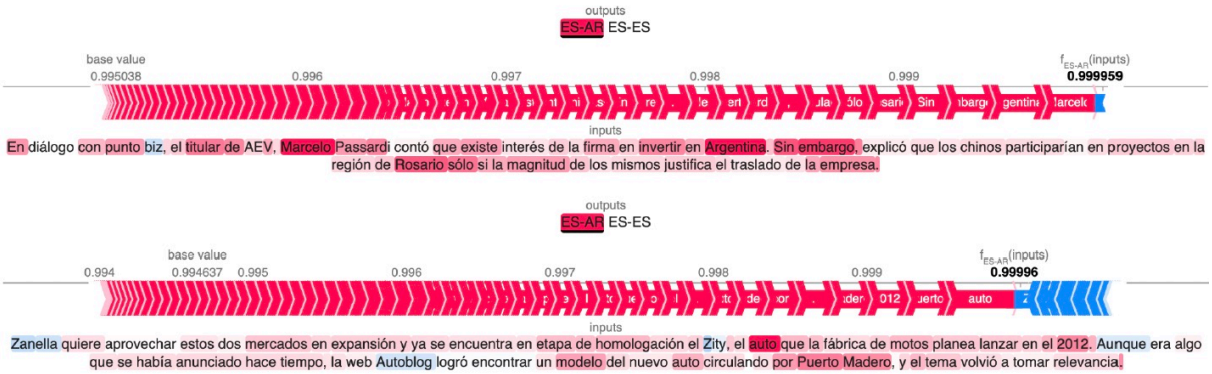


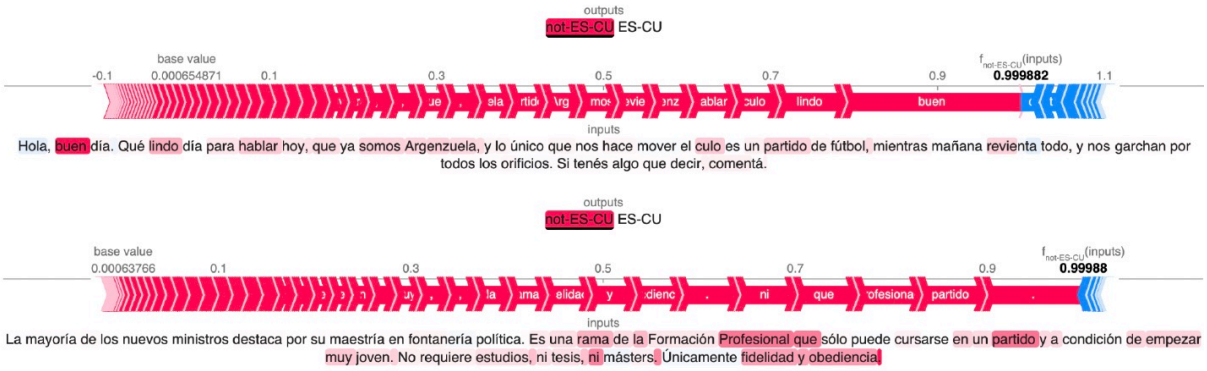

Figure 8: Agreement index for error instances in Top-N using $DM_{mean}$ score metric.

in the DSL-TL dataset ranking. For the first example, the words *Argentina*, *Rosario*, and *Marcelo* are the most influential for predicting the *ES-AR* label. The first two refer to the country and one of its major cities, while *Marcelo* is a common name in Argentina. For the second example, *auto* (commonly used in Argentina to mean "car," as opposed to *coche* in Spain) is the most significant feature, followed by *Puerto* and *Madero*, a well-known place in Argentina. While named entities influence the first example, the second example, with the word *auto*, suggests a potential annotation error, as it points to the Argentinian variant.

In Figure 9b, we provide the corresponding analysis for the CUBANSPVARIANT dataset. For the first example, the word *buen* (from the phrase *buen día*, which is used in Spanish variants other than the Cuban one) is the most significant, along with *Argenzuela* (a blend of Argentina and Venezuela), *garchan*, and *tenés*, which are characteristic of the




(a) DSL-TL dataset examples.




(b) CUBANSPVARIANT dataset examples.

Figure 9: For each dataset, we analyze the last two common examples in the ranking obtained using $DM_{mean-pred}$. The model is trained on binary classification for variant detection. The final output of the models for the predicted variant/class is highlighted. Red-colored terms influence the final decision towards *ES-ES* or *ES-CU* depending on the dataset, while blue-colored terms influence the model classification towards *ES-AR* or *not-ES-CU* classes.

Argentinian variant. This example likely represents an annotation mistake. For the second example, the most influential words are *profesional*, *partido*, *fidelidad*, and *obediencia*, none of which are strong indicators of a specific variant. This suggests that common topics in Cuban tweets may affect the model's prediction, potentially introducing biases into the classification process.

## 7 Conclusion

In this work, we examine the effectiveness of Datamaps methods in identifying common examples across closely related language variants. Our results demonstrate the value of training dynamics in detecting difficult examples early in the model's learning process, as reflected by the effectiveness of $DM_{\text{mean-pred}}$ across both datasets. This confidence-based approach consistently outperformed the variability-based method, suggesting that tracking model confidence over predicted labels offers a reliable way to identify common examples automatically across different domains. While the performance difference between variability and confidence-based approaches is less significant for the informal dataset, the overall results indicate that confidence-based Datamaps can be a powerful tool for improving data quality in different contexts.

Although these methods may not fully solve the challenges of variant and dialect annotation, they offer a promising step forward, particularly when combined with automatic techniques and targeted human annotation.

We hope that this initial dataset, freely accessible under a CC-BY-SA license upon publication, the first centered on Cuban, a Caribbean variant of Spanish, will prove a valuable resource for future research on this topic.

## 8 Limitations

One limitation of our work is that the analysis focuses on binary classification scenarios, explicitly distinguishing between two main classes in each dataset without incorporating multi-class approaches or more complex variant distinctions. While this setup allows us to study common examples effectively, expanding the approach to multi-variant settings could provide a more comprehensive understanding of the challenges posed by language variant identification.

Another limitation is inherent to way the CUBANSPVARIANT dataset annotations were built. Since all annotators were Cuban native speakers, the dataset focuses on Cuban versus non-Cuban distinctions. Incorporating annotators from other Spanish-speaking regions would allow for broader variant distinctions and more nuanced annotations, which could reduce potential biases introduced by a single-region perspective.

Finally, as discussed in Section 6, named entities, including hashtags, play a significant role in model behavior. Managing these entities, such as replacing them with special tokens, could be an effective way to reduce bias and improve generalization. This is especially important in tasks like language variant classification, where named entities might disproportionately influence predictions.

## 9 Ethical Considerations

This work involves using social media data, particularly from Twitter, which may contain sensitive or controversial content. Although we anonymize the data by replacing user mentions and URLs, the content could still involve personal opinions, political statements, or even hate speech, especially in datasets like the CUBANSPVARIANT dataset, which includes tweets related to politically sensitive events such as the July 11th protests in Cuba. Given the nature of the protests, some tweets may contain offensive content. We are aware of the potential privacy implications when working with such data, and we have adhered to Twitter's data usage policy to ensure compliance with ethical standards. Researchers accessing this dataset should consider the ethical implications when using politically charged content or messages that might harm individuals or communities.

Furthermore, identifying language variants, especially in socially and politically sensitive contexts, risks reinforcing stereotypes or biases associated with particular regions or dialects. In this work, we frame our approach as a technical solution for linguistic diversity and not as a tool for making any sociopolitical or cultural assumptions about the speakers of these variants. However, we acknowledge that any automated system trained on real-world data is susceptible to unintended biases arising from imbalanced datasets or biased annotations. The annotations in the CUBANSPVARIANT dataset are from native Cuban speakers, and while this helps in identifying Cuban Spanish, it may introduce a regional bias.

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## A Data Preprocessing:

Following previous works (Pérez et al., 2022; Castillo-lópez et al., 2023), we pre-processed the data by replacing user mentions with the token *@usuario* (or *@user* in English), allowing up to two consecutive mentions. URLs were substituted with the token *url*, and hashtags were segmented into words assuming Camel Case typing (e.g., #CubaIsLaBella becomes *Cuba isla bella*). Emojis were replaced with their corresponding descriptions using the *emoji* python library [4], and any repeated emojis were removed. Laughs were normalized to *jaja*, following the standard in Spanish, and for letter repetitions, we kept up to two. We also removed repeated spaces and replaced line breaks with periods.

[4] Emoji python library website.

| | |
|---|---|
| #sentences | 1762 |
| #tokens | 41374 |
| Avg length | 23.48 |
| Length variation (std) | 13.49 |
| Vocab size (unique words) | 13336 |

Table 2: DSL-TL Overview.

## B Annotation Guidelines for DSL-TL

The following guidelines were provided to the annotators to ensure consistent labeling of the dataset:

- **cuban_variant**: A boolean value indicating whether the tweet belongs to the target Spanish variant (Cuban). This value should be set to *true* only if the annotator can clearly identify evidence that the tweet belongs to the Cuban variant.
- **not_cuban_variant**: A boolean value indicating that the tweet does not belong to the target Cuban variant. This value should be set to *true* only if it is clear that the tweet does not belong to the Cuban variant, even if the specific variant cannot be identified.
- **specific_variant**: A string indicating the specific variant if the annotator can easily identify it. The value should remain empty if the specific variant cannot be identified. The possible variants are based on the Spanish variants map presented in the appendix of *Analyzing Zero-Shot Transfer Scenarios Across Spanish Variants for Hate Speech Detection*. These are:
  - Other Caribbean variant
  - Central American variants (Costa Rica, El Salvador, Panamá)
  - Mexican
  - Spain
  - Rioplatense (Argentina, Uruguay)
  - Chilean
  - Habla de las tierras altas (Perú, Venezuela, Colombia, Bolivia, Ecuador)
- **unable_to_identify_variant**: A boolean value set to *true* if the annotator cannot identify any specific variant for the tweet.
- **irrelevant**: A boolean value set to *true* if the tweet's content is considered irrelevant. This can be due to the tweet's size or other characteristics that lead to a lack of meaningful content.

| Annotator | Age | Gender |
|---|---|---|
| Annotator 1 | 26 | Male |
| Annotator 2 | 26 | Female |
| Annotator 3 | 23 | Female |

Table 3: Socio-demographic attributes of the annotators

| Hyper-parameter | Value |
|---|---|
| Max sequence length | 512 |
| Batch size | 32 |
| FP16 | Enabled |
| Learning rate | 1e-5 |
| Epochs | 10 |
| Scheduler | linear |
| Warmup ratio | 0.1 |
| Weight decay | 0.01 |
| Save strategy | Epoch |
| Logging steps | 10 |
| Seed | {42,151,2021,15,98} |

Table 4: Hyper-parameters used for the fine-tuning.

# C Hyper-parameters

The model will be released under the Creative Commons CC-BY-SA license, allowing for open access and use with appropriate attribution.

All experiments were conducted using a single NVIDIA RTX 8000 GPU, with each experiment taking less than two hours to complete. We used the `AutoModelForSequenceClassification` from Hugging Face's Transformers library (Wolf et al., 2020) for sequence classification tasks.

# D Variant Identification Results

## D.1 Variant Identification Benchmarks on CubanSpVariant dataset

In this section, we present the benchmark results for the CubanSpVariant dataset. We use the same experimental setting for this task, as explained before. We present the dataset's benchmark for both approaches, single and multi-class. For the multi-class approach, we follow the procedure suggested by Keleg and Magdy (2023); Bernier-colborne et al. (2023) of using one binary classifier per label. For the metrics, we used the macro average across all possible variants.

Table 5 shows the final results. We can notice a significant improvement in the model's performance in the multi-class scenario. This strengthens the point about single-class approach limitations for variant identification.

## D.2 Variant Identification Benchmarks on DSL-TL dataset

In this section, we present the benchmark results for the DSL-TL dataset. Table 6 shows the final results. As for the CubanSpVariant dataset, there is a significant improvement in the model's performance in the multi-class scenario.

| Approach | Acc | Precision | Recall | f1-score |
|---|---|---|---|---|
| single-class | 67.54 ± 1.42 | 65.86 ± 1.69 | 64.45 ± 1.01 | 64.62 ± 1.05 |
| multi-class | **78.69 ± 0.86** | **82.64 ± 0.91** | **87.80 ± 1.28** | **85.06 ± 0.61** |

Table 5: Benchmarks for Variant Identification task on CUBANSPVARIANT dataset. We present the results for both the single-class and the multi-class approaches.

| Approach | Acc | Precision | Recall | f1-score |
|---|---|---|---|---|
| single-class | 76.76 ± 0.74 | 76.18 ± 0.80 | 75.78 ± 0.75 | 76.76 ± 0.74 |
| multi-class | **77.65 ± 0.27** | **82.00 ± 0.29** | **83.99 ± 0.30** | **82.97 ± 0.25** |

Table 6: Benchmarks for Variant Identification task on DSL-TL dataset. We present the results for both the single-class and the multi-class approaches.