

# Dialect Normalization using Large Language Models and Morphological Rules

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## Abstract

Natural language understanding systems struggle with low-resource languages, including many dialects of high-resource ones. Dialect-to-standard normalization attempts to tackle this issue by transforming dialectal text so that it can be used by standard-language tools downstream. In this study, we tackle this task by introducing a new normalization method that combines rule-based linguistically informed transformations and large language models (LLMs) with targeted few-shot prompting, without requiring any parallel data. We implement our method for Greek dialects and apply it on a dataset of regional proverbs, evaluating the outputs using human annotators. We then use this dataset to conduct downstream experiments, finding that previous results regarding these proverbs relied solely on superficial linguistic information, including orthographic artifacts, while new observations can still be made through the remaining semantics.<sup>1</sup>

## 1 Introduction

Natural language processing has long struggled with lower-resource language varieties, including geographic varieties of higher-resource standardized ones (Joshi et al., 2025). According to members of such language communities, who are usually also speakers of the equivalent standard, natural language understanding (NLU) of dialectal text is much more important than language generation (NLG) into the local variety (Blaschke et al., 2024).

This variation in demand highlights the significance of transforming dialectal text into a standard variety while maintaining as much of the original meaning as possible, which is known as dialect-to-standard normalization. That is because by improving our methods in this area we will be able to apply modern NLU techniques to a vast array of formerly

<sup>1</sup>We publicly release all code and datasets produced for this work: [https://github.com/andhmak/rule\\_dialnorm](https://github.com/andhmak/rule_dialnorm)

### Source Dialectal Sentence

src: Οὐ Θεός κι ου γείτονας.  
/u theós ki u jítonas/  
*God and the neighbour.*

### Baseline Normalization

→: Ούτε ο Θεός, ούτε ο γείτονας. ✗  
/úte o theós, úte o jítonas/  
*Neither God nor the neighbour.*

### Proposed Rule-Enhanced Method

→ Ο Θεός και ο γείτονας. ✓  
/o theós ke o jítonas/  
*God and the neighbour.*

Figure 1: Predictable phonological changes (/o/→/u/) in Northern Greek dialects make the definite article “o” appear closer to Standard “ούτε” (/úte/, *neither*). We combine LLMs with rule-based normalization to better understand dialectal sentences.

neglected varieties through models trained on data of their related standard languages.

In this work, we introduce a novel method for normalizing dialectal data into a standard variety. Our proposed method first applies morphological rules, specified based on dialect-specific linguistic prior knowledge, and then feeds the preprocessed input to an LLM along with dialect-specific shots. This second step enhances the input with sentences exhibiting those facultative dialectal features which are not addressable only with the first step.

We implement the language-specific parts of this procedure for a set of Greek dialects represented in a large dataset of regional proverbs. An example of our method compared to simple prompting for one of the proverbs in our dataset is shown in Figure 1. We then experiment with two different LLMs and ablate the rule-based step, using human annotators. We thus produce a new normalized dataset in Standard Modern Greek, which we use in downstream tasks: first, we replicate prior research using the newly-standardized proverbs to ascertain whether the previous results depended on the semantics or on the now-removed linguistic peculiarities of each variety and its transcription method.

Additionally, we conduct further experiments showcasing the usability of our dataset for obtaining semantic, non-dialectally-colored insights into a set of originally dialectal texts.

In short, we make the following contributions:

- We propose a new method for normalizing dialectal speech, using a pipeline of rule-based transformations followed by an LLM with a few dialect-specific examples.
- As a proof-of-concept, we implement the linguistic rules for Greek dialects and run our pipeline on a dataset of Greek proverbs, producing a normalized dataset of regional proverbs, validated using human annotations.
- We show that previous observations into the original dataset could have been influenced by dialectal linguistic features, which disappear in the standardized text, while new, mainly semantic-based insights are possible.

## 2 Related Work

Previous work has been carried out in the area of dialect normalization, targeting specific varieties (Abdul-Mageed et al., 2023; Partanen et al., 2019; Scherrer and Ljubešić, 2016), as well as more generalized approaches (Kuparinen et al., 2023).

Recently, pretrained multilingual LLMs have proven useful in such tasks, especially when fine-tuned on parallel dialectal-standard data (Ibn Alam and Anastasopoulos, 2025). These kinds of parallel datasets are in some way or another required in all these past techniques in order to train specialized models. In contrast, our technique eliminates this requirement by leveraging LLMs' tendency to treat unseen dialectal features as noise, combined with the exploitation of linguistic knowledge of the dialects in question and as few as three parallel sentences for few-shot prompting. This makes our approach viable even for use cases such as the one we explore where there are practically no parallel text data available.

Pavlopoulos et al. (2024) introduced a machine-actionable dataset of Greek proverbs, comprising over 100,000 proverb variants, each originating from one of 134 unique locations across Greece. An exploration of the spatial distribution of proverbs showed that the most widespread proverbs come from the mainland while the least come primarily from the islands. Using the latter, then, they showed that text geolocation/geocoding (Hovy and Purschke, 2018; Han et al., 2016; Chakravarthi

et al., 2021; Ramponi and Casula, 2023) can be accurate for specific locations, and that conventional machine learning algorithms operating on stylistic features outperformed transfer learning. We argue, however, that relying on the superficial linguistic features of the original (non-normalized) text, instead of semantic ones, makes it hard to determine shared semantics or any (possibly deeper) cultural connections across different regions.

## 3 Methodology

Our normalization method consists of two steps. First, we preprocess our inputs using a rule-based procedure. Then, we pass the previous step's output to an LLM with few-shot prompting.

**Part 1: Rule-based normalization (RBN)** RBN is achieved by string replacements of specific character sequences according to the linguistic features of each dialect compared to the standard. We divide the Greek dialects into three groups, following established literature (Trudgill, 2003): Northern, Southern and Pontic, according to their features, and use different transformation rules for each group. The dialects' specific distribution among these groups is described in Appendix A, and indicative examples of string replacements are in Appendix B. The amount of linguistic knowledge required is roughly what would be present in a dialect's comparative grammar, in our case amounting to 14 string replacement rules.

**Part 2: Few-shot prompting** Our prompts are designed to guide the model to perform our desired task while also providing the LLM with the necessary linguistic information, which is otherwise difficult to encode using rules. First, we include the name of the region our text is sourced from (especially helpful if the model has seen relevant data during pre-training). Second, we provide instructions to only change the dialect, so that it conforms with the standard, without affecting the style of the text. Otherwise, we notice that LLMs tend to view dialectal features as signs of informality, and therefore produce overly formal text when not explicitly directed not to. Similarly, they seem to replace vocabulary existing in both the dialect and the standard with alternatives. Hence, we also instruct for lexical terms to only be replaced when they are absent from the standard. Finally, we provide a few examples of the task being performed successfully, specifically selected to display dialectal features

not encoded in the previous step. The full prompt used per dialectal group is provided in Appendix C.

## 4 Normalization Experiments

**Dataset** We perform our experiments on the dataset provided by Pavlopoulos et al. (2024), specifically on the balanced corpus, containing 500 proverbs from each geographic location, which was also used for their experiments.

**Models** For the LLM-based part of our normalization method, we use **GPT-4o** (gpt-4o-2024-11-20; OpenAI et al., 2024) as well as the **Llama 3.1-70B** (Grattafiori et al., 2024). Overall we explore four different setups:

1. **GPT 3s+RBN** uses GPT-4o and follows the entire pipeline as described in Section 3;
2. **GPT 3s** only uses the 3-shot prompting method, using a different prompt according to the group of the input dialect, skipping RBN;
3. **Llama 3s+RBN** uses Llama 3 and also follows the entire pipeline; and
4. **Llama 9s** uses Llama 3 and skips both RBN and the division into dialectal groups, providing all three parallel examples of all three dialectal groups in every prompt.

**Human evaluation** We employed three native Greek speakers to evaluate a subset of the normalized proverb dataset. For each sentence, normalized with each of the four setups, they were instructed to provide a score from 1 to 5 on two axes. One was “form”, referring to how well the normalized sentence was stripped of its dialectal features and rendered into fluent Standard Modern Greek. The other was “meaning”, referring to how well the original meaning of the dialectal sentence, including its style, was preserved in the normalized one. For each of these two axes, they were also asked to choose the best normalized sentence out of the four, with ties only allowed in case of identical output strings. We derived various statistical measures guaranteeing the reliability of the annotations, inter-annotator agreement, and statistical significance. Table 1 depicts the high Intraclass Correlation Coefficients (ICC) calculated on the annotations for each model on both axes, and more detailed results can be found in Appendix D.

**Results** Table 2, on the left, depicts the average human evaluation from 1 (worst) to 5 (best), based on form and meaning. The percentage each setup was assessed by human evaluators as the

| Model        | Form ICC | Meaning ICC |
|--------------|----------|-------------|
| GPT 3s+RBM   | 0.884    | 0.783       |
| GPT 3s       | 0.934    | 0.893       |
| Llama 3s+RBN | 0.790    | 0.910       |
| Llama 9s     | 0.888    | 0.875       |

Table 1: ICC for “form” and “meaning” ratings per model. Values closer to 1 indicate better correlation.

| Model        | Normalization Quality (out of 5) |             | Percentage Best (%) |             |
|--------------|----------------------------------|-------------|---------------------|-------------|
|              | Form                             | Meaning     | Form                | Meaning     |
| GPT 3s+RBN   | <b>4.68</b>                      | <b>4.62</b> | <b>88.3</b>         | <b>91.5</b> |
| GPT 3s       | 4.46                             | 4.26        | 66.8                | 68.6        |
| Llama 3s+RBN | 3.1                              | 3           | 16.7                | 13.5        |
| Llama 9s     | 2.52                             | 2.34        | 9.3                 | 9.7         |

Table 2: Average human evaluation, from 1 to 5 (best), regarding the form and meaning of the output per setup. GPT 3s+RBN is the best (left) and its output is the preferred normalization about 90% of the time (right).

best (for form and meaning) is shown on the right. GPT 3s+RBN was the best in form and meaning, followed by GPT 3s, Llama 3s+RBN and Llama 9s. Differences among models are more prominent when explicitly asking for a preferred output.

## 5 Downstream tasks

### 5.1 Text Geocoding/Geolocation

We replicated the experiments of Pavlopoulos et al. (2024), by using their corpus but normalizing it with our best performing approach (GPT 3s+RBN). This includes training models for: (a) predicting the region label for each proverb without providing any further geographic information; and (b) for predicting the geographic coordinates using regression, after providing each region’s exact location. After removing any non-semantic and dialectal information (i.e., normalizing), we find that geolocation methods fail. This finding verifies the hypothesis of Pavlopoulos et al. (2024) about predictions being based on linguistic information.

**In the classification geolocation task**, using the non-normalized data, the best model reaches an average F<sub>1</sub> score of 0.33, with that of specific regions being as high as 0.81. Using normalized data, however, the best model reaches only 0.13 (see Table 3), with no region going above 0.35.

**In the regression geolocation task**, performance decreased less, going from an average root mean square error of 2.9 to 3.2 (see Table 4). The full results can be found in Appendix H.

**Semantic or superficial?** Compared to the results of the non-normalized analysis, models trained on our normalized data rely more on semantic, rather than on superficial linguistic features, such as transcription conventions. For instance, the top four terms guiding the best geolocation model (trained on non-normalized data) Southwards comprise different transcriptions of the conjunction  $\kappa\alpha\iota$  (kai, and). That is, they are phonologically affected by the Southern phenomenon of velar palatalization. However, when the same model is trained on the normalized version, it utilizes mainly semantically meaningful content words.

| Model               | Dialectal F <sub>1</sub> | Normalized F <sub>1</sub> |
|---------------------|--------------------------|---------------------------|
| Logistic Regression | <b>0.29</b>              | 0.12                      |
| SVM                 | <b>0.33</b>              | 0.13                      |
| K Nearest Neighbors | <b>0.23</b>              | 0.11                      |
| Random Forest       | <b>0.25</b>              | 0.13                      |

Table 3: Average F<sub>1</sub> per model for region (label) prediction, using the original dialectal dataset and our normalized one. Classification is harder after removing superficial linguistic information.

| Model               | Dial Avg RMSE | Norm Avg RMSE |
|---------------------|---------------|---------------|
| ElasticNet          | <b>2.93</b>   | 3.25          |
| K Nearest Neighbors | <b>3.16</b>   | 3.24          |
| Linear Regression   | <b>2.97</b>   | 3.32          |
| Random Forest       | <b>2.98</b>   | 3.20          |
| ERT                 | <b>2.99</b>   | 3.23          |

Table 4: Average root mean square error (RMSE) per model for coordinate regression, using the original dialectal dataset and our normalized one. Regression is harder after removing superficial linguistic information, but not as much as classification.

## 5.2 Region Clustering

Using **GreekBERT**, a monolingual encoder-only model for Standard Modern Greek (Koutsikakis et al., 2020), we construct a dense representation for each proverb by averaging the embeddings of its tokens. We then average the representations of all proverbs for each region to create representations of the regions themselves, and perform clustering of the regions. As input, we use both the original corpus provided in our dataset, as well as the normalized one. No geolocation data is provided; only the text of the proverbs from each region.

Using K-means and the Silhouette method, we find the best results in both dataset versions are obtained for  $k = 2$ . The outputs of other algorithms,

including of K-means for different values of K, can be found in Appendix G. The output of the algorithm using the two versions of the data is shown in Figure 2. Based on these depictions, we consider that the results are far more meaningful when the data are normalized first. Using the original dialectal data, Pontus and Cyprus, two distant and unrelated regions, are put together in one cluster, and everything else is clustered together. With our normalized version, one cluster consists of islands and coastal regions, and the other of mainland ones. The few outliers, such as Skyros and Lesbos, are not random either. Despite being islands, they appear in the “mainland” cluster, but they are also the only islands in our dataset that have historically had significant connections with the Northern mainland. Overall, while there is no clearly discernible geographic information in the PCA plot produced using the dialectal data, the normalized one seems to have roughly put Western and Northern regions on the top and left, while Eastern and Southern ones are on the bottom and right. This implies that we can now uncover geographic information through the semantic similarity of proverbs.

## 5.3 Cardinal direction driving words

We also fine-tune GreekBERT (see Appendix I) to predict geographic coordinates (as in §5.1, achieving a mean absolute error of 1.59). To analyze which tokens guide this model towards each cardinal direction, we iterate over the dataset and mask each token in every proverb, averaging the change in the predicted coordinates, in a method similar to input erasure (Pavlopoulos et al., 2021). We find meaningful results, such as the words for “cold” and “winter” being among the most influential ones in pushing the prediction to the North, which has a significantly colder climate.

## 6 Discussion and Future Work

Our experimental results show that our full setup outclasses all tested baselines in terms of both form normalization and meaning conservation, but also independently achieves performance similar to an ideal human expert (who would have achieved scores close to the 5-point mark). This, along with the results achieved in downstream tasks, indicates that our approach can be used in various contexts for dialectal NLU as an upstream method.

When it comes to the downstream experiments, we hypothesize that the difference in performance

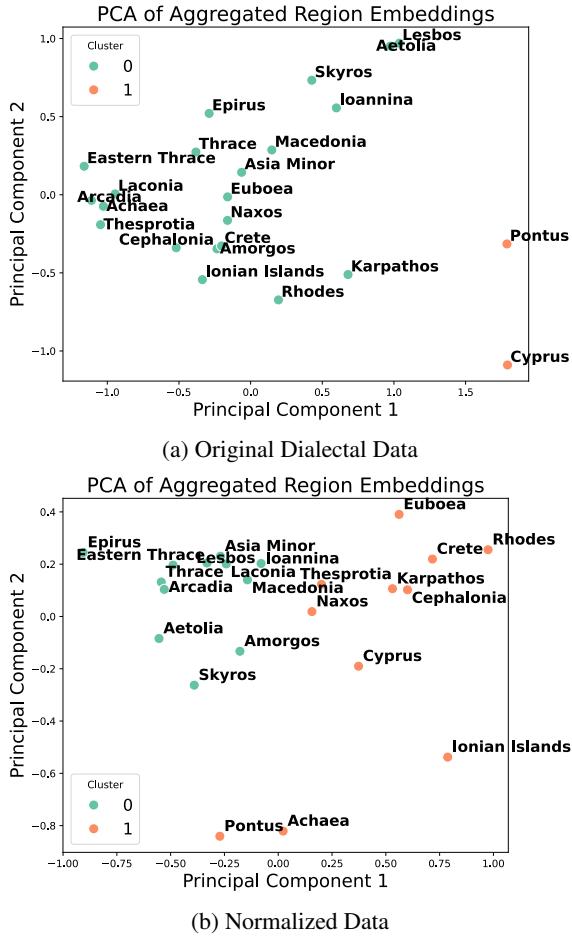


Figure 2:  $k$ -means clustering with normalized data produces more reasonable clusters (full size in App. F).

between the old and new ones has to do with the different methods of dialectal transcription used for each region. Even though they appear to offer very clear signals for recognizing each area specifically, they obfuscate existing dialectal and cultural similarities. Therefore, when using normalized data, it is impossible to pinpoint exactly the area where a specific proverb originates from, as they are often widely shared. Conversely, it is much easier to categorize the regions themselves, as by removing the layer of transcription, which previously created unrelated “islands” for each specific region, interregional parallels can be detected.

Our method adds little additional overhead, monetary or temporal, to the baseline of simply using an LLM for the task, as RBN can be executed within seconds for our entire dataset on a consumer CPU.

Based on feedback from our annotators, we notice that the main failure case is sentences containing dialectal vocabulary without a clear cognate in Standard Modern Greek. Since such rare vocabu-

lary does not appear in any of the LLMs’ training data with sufficient frequency so that its meaning can be learned, and morphological rules cannot address purely lexical divergence from the standard, the model is left to infer the meaning from the surrounding context.

**Future Work** We believe that it would be worthwhile to create comprehensive dictionaries of dialectal terms which do not appear in the standard, especially for varieties that are overall relatively close linguistically to a higher-resource language, in cases where they do not already exist (as is the case for most Greek dialects).

Given that our results indicate that this is the main issue currently complicating automatic processing for these dialects, at least when it comes to their understanding, such a resource could be a crucial tool in finally extending coverage to many underserved linguistic communities.

## Limitations

We acknowledge that since the evaluators do not have native knowledge of all Greek dialects, they may have missed some of the subtle meanings of the proverbs whose translations they were evaluating. The sentences are, however, mostly understandable by all Greek speakers, and much of the normalization consisted of conforming to standard spelling.

Moreover, as mentioned above, our method may produce sub-par results in cases where rare dialectal vocabulary with no cognate in the standard is used.

## Ethics Statement

The very nature of the dialect-to-standard normalization task means that at least some sociolinguistic signals will be erased from the input, which risks contributing to the global decline in linguistic diversity. We do not consider this to be a significant additional risk, as our method is intended for Natural Language Understanding specifically. LLMs cannot on their own, using current architectures, learn such low-resource varieties, and dialectal text given to them in the form of prompts is already being stripped of much of its form and meaning by the model’s internal processing. Our method is not intended for Natural Language Generation, which is to say, it would not cause a model to produce normalized instead of dialectal text, but it would help it better understand the dialect, which research

indicates is the desire of the majority of dialectal speakers.

We have obtained permission from all annotators to publish the data they produced in the context of this paper. The annotators were volunteers, and no monetary compensation was provided for their involvement.

The content of the Greek Proverb Atlas Dataset is available under a CC BY-NC-ND 4.0 license, in csv format. Its usage in this project is therefore consistent with its intended use. All models we use come with permissive licenses, at least when it comes to research.

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## A Dialect Groups

### A.1 Northern

This includes: Macedonia, Thrace, Eastern Thrace, Skyros, Epirus, Ioannina, Asia Minor, Aetolia, Euboea and Lesbos.

### A.2 Southern

This includes: Amorgos, Arcadia, Achaea, Ionian Islands, Thesprotia, Karpathos, Cephalonia, Crete, Cyprus, Laconia, Naxos and Rhodes.

### A.3 Pontus

This includes Pontus, a very divergent dialect which doesn't share many features with the others.

## B Major Changes per Dialect Group

Below is one major example of the changes our scripts make for each group:

### B.1 Northern

A major characteristic of Northern dialects is “Northern vocalism”, which raises standard mid vowels (/ɔ/, /e/) to high vowels (/u/, /i/) in unstressed positions, while original high vowels disappear under the same circumstances. Completely undoing this rule is difficult, as it is facultative and therefore not reversible. However, there are certain patterns, such as the word /u/ followed by another ending in unstressed /-us/, which are almost guaranteed to be the result of this rule, and are therefore safe to reverse to /ɔ/ and /-os/ at this stage.

### B.2 Southern

A feature of Southern dialects is the palatalization of velars, especially /k/, before vowels (/ɛ/, /i/). The resulting palatal is represented differently in each dialect due to the decisions of each transcriber who happened to collect data from each region. Similarly to above, it is difficult to know which palatal was original or resulted from this rule, so the process is not completely reversible, but we revert it in specific cases where it is almost certain.

### B.3 Pontus

Pontic Greek uses /do/ in place of Standard Modern Greek /ti/ (meaning “what”), while in other dialects this usually represents a voiced version of the definite article.

## C Full Prompt Templates

We used the following three prompt templates, one for each group of Greek dialects. “<place>” is replaced by the area label, while “<text>” is replaced by the source dialectal proverb.

### C.1 Northern

‘Given a Greek sentence from <place>. Translate it to standard Greek. Keep the same style, do not make it more official. Use words with the same etymology if and only if they exist in standard Greek, otherwise use different words. Show just the translation and nothing else.

For example:

<place>: Γίδα ψουράρα, νουρά  
χορδούμεν'

Standard Greek: Γίδα φωριάρα, ουρά  
χορδωμένη

<place>: Μι πήρι, σι πήρι, τουν πήρι  
του πουτάμ'

Standard Greek: Με πήρε, σε πήρε,  
τον πήρε το ποτάμι

<place>: Τ' γάμσι του κέρατου

Standard Greek: Του γάμησε το  
κέρατο

<place>: <text>

Standard Greek:’

### C.2 Southern

‘Given a Greek sentence from <place>. Translate it to standard Greek. Keep the same style, do not make it more official. Use words with the same etymology if and only if they exist in standard Greek, otherwise use different words. Show just the translation and nothing else.

For example:

<place>: Καλλιά 'ν το διωκονίκι, παρά  
το βασιλίκι

Standard Greek: Καλύτερα είναι το  
διωκονίκι, παρά το βασιλίκι

<place>: Τάχει η γραι στο λοϊσμό τζη  
τα θωρεί και στο όνειρό τζη

Standard Greek: Τάχει η γραι στον  
λογισμό της τα βλέπει και στο όνειρό  
της

<place>: Των βρενίμων τα παιδιά  
πριν πεινασουν μαειρέύκουν

Standard Greek: Των φρονίμων τα  
παιδιά πριν πεινάσουν μαγειρεύουν

<place>: <proverb>

Standard Greek:’

### C.3 Pontus

‘Given a Greek sentence from Πόντος. Translate it to standard Greek. Keep the same style, do not make it more official. Use words with the same etymology if and only if they exist in standard Greek, otherwise use different words. Show just the translation and nothing else.

For example:

Πόντος: Ποιος βάλλ' το χέρ' ατ' 'ς σο  
μέλ' και 'κι λείχ' τα δάχτυλα τ'

Standard Greek: Ποιος βάζει το χέρι  
του στο μέλι και δεν γλείφει τα  
δάχτυλά του

Πόντος: Κιάν παθάνης κι μαθάνεις

Standard Greek: Αν δεν παθάνεις δεν  
μαθάνεις

Πόντος: Ο νέον θολόν ποτάμιν είναι!

Standard Greek: Ο νέος θολό ποτάμι  
είναι!

Πόντος: <proverb>

Standard Greek:’

## D Detailed Annotation Statistics

### D.1 Pearson Correlations

We report the average pairwise Pearson Correlation for the ratings of the outputs of each model among the three annotators.

Numbers closer to 1 indicate better correlation.

#### D.1.1 Form

| Model        | Pearson |
|--------------|---------|
| GPT 3s+RBN   | 0.733   |
| GPT 3s       | 0.822   |
| Llama 3s+RBN | 0.601   |
| Llama 9s     | 0.787   |

Table 5: Average Pearson Correlation for each model.

### D.1.2 Meaning

| Model        | Pearson |
|--------------|---------|
| GPT 3s+RBN   | 0.646   |
| GPT 3s       | 0.731   |
| Llama 3s+RBN | 0.821   |
| Llama 9s     | 0.762   |

Table 6: Average Pearson Correlation for each model.

### D.2 Intraclass Correlation Coefficients

We specifically report the ICC (2,k) statistic, calculated for the average of ratings provided by a set of annotators, where the annotators are treated as random effects under a two-way random effects model. This is because we use the average of their evaluations in our analyses instead of any specific individual rating, while our annotators are used as representatives of the Greek-speaking population, and we are interested in their evaluations as part of this group.

Numbers closer to 1 indicate better correlation, with 0.75 to 0.9 generally considered good, and higher than 0.90 excellent (Koo and Li, 2016).

#### D.2.1 Form

| Model        | ICC   | F      | df1 | df2 | p                      | CI95%        |
|--------------|-------|--------|-----|-----|------------------------|--------------|
| GPT 3s+RBN   | 0.884 | 8.819  | 26  | 52  | $2.24 \times 10^{-11}$ | [0.78, 0.94] |
| GPT 3s       | 0.934 | 14.700 | 26  | 52  | $6.77 \times 10^{-16}$ | [0.87, 0.97] |
| Llama 3s+RBN | 0.790 | 5.201  | 26  | 52  | $2.24 \times 10^{-7}$  | [0.60, 0.90] |
| Llama 9s     | 0.888 | 11.264 | 26  | 52  | $1.79 \times 10^{-13}$ | [0.76, 0.95] |

Table 7: ICC (2,k) and the associated F-statistic, numerator (df1) and denominator (df2) degrees of freedom, p-value (for the possibility of the true ICC being 0) and 95% confidence interval for the form ratings of each model.

#### D.2.2 Meaning

| Model        | ICC   | F      | df1 | df2 | p                      | CI95%        |
|--------------|-------|--------|-----|-----|------------------------|--------------|
| GPT 3s+RBN   | 0.783 | 4.667  | 26  | 52  | $1.00 \times 10^{-6}$  | [0.59, 0.89] |
| GPT 3s       | 0.893 | 9.065  | 26  | 52  | $1.32 \times 10^{-11}$ | [0.80, 0.95] |
| Llama 3s+RBN | 0.910 | 12.133 | 26  | 52  | $3.90 \times 10^{-14}$ | [0.83, 0.96] |
| Llama 9s     | 0.875 | 9.679  | 26  | 52  | $3.71 \times 10^{-12}$ | [0.75, 0.94] |

Table 8: ICC (2,k) and the associated F-statistic, numerator (df1) and denominator (df2) degrees of freedom, p-value (for the possibility of the true ICC being 0) and 95% confidence interval for the meaning ratings of each model.

### D.3 Paired T-Tests for Statistical Significance

We report on the statistical significance of each model’s score being higher than the following in the sequence in which they were ranked.

P-values  $< 0.05$  are typically considered statistically significant.

#### D.3.1 Form

| Model                 | t-statistic | p-value               |
|-----------------------|-------------|-----------------------|
| GPT (3s+RBN - 3s)     | 2.083       | 0.041                 |
| GPT 3s - Llama 3s+RBN | 9.385       | $1.9 \times 10^{-14}$ |
| Llama (3s+RBN - 9s)   | 3.295       | 0.001                 |

Table 9: Statistical significance of each model’s form-score being higher than the following in the sequence in which they were ranked. All p-values are  $< 0.05$ .

#### D.3.2 Meaning

| Model                 | t-statistic | p-value               |
|-----------------------|-------------|-----------------------|
| GPT (3s+RBN - 3s)     | 3.202       | 0.002                 |
| GPT 3s - Llama 3s+RBN | 7.157       | $3.9 \times 10^{-10}$ |
| Llama (3s+RBN - 9s)   | 3.373       | 0.001                 |

Table 10: Statistical significance of each model’s meaning-score being higher than the following in the sequence in which they were ranked. All p-values are  $< 0.05$ .

## E Demographic details of the annotators

Out of our three annotators, two were native speakers of Standard Modern Greek and the Cretan dialect, while the other was a native speaker of Standard Modern Greek and Northern Greek. The contents of our dataset are generally understandable to all Greek speakers.

## F Results of K-means for 2 clusters (full size)

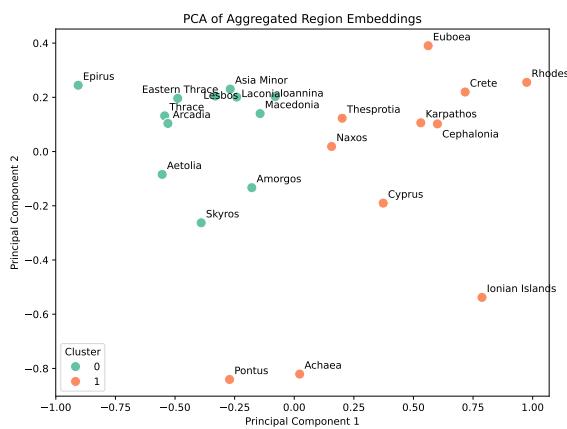


Figure 3: K-means clustering for 2 clusters using normalized data

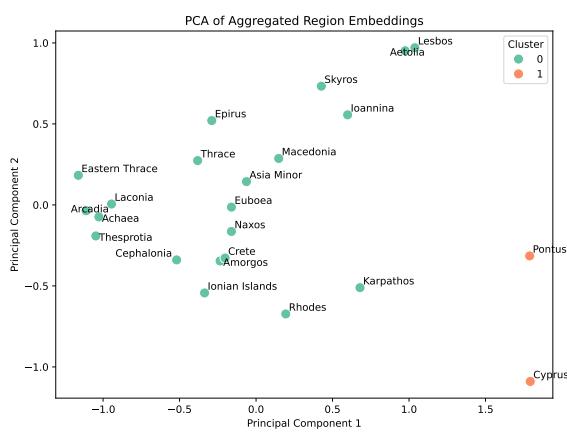


Figure 4: K-means clustering for 2 clusters using original dialectal data

## G Results of other Clustering Algorithms

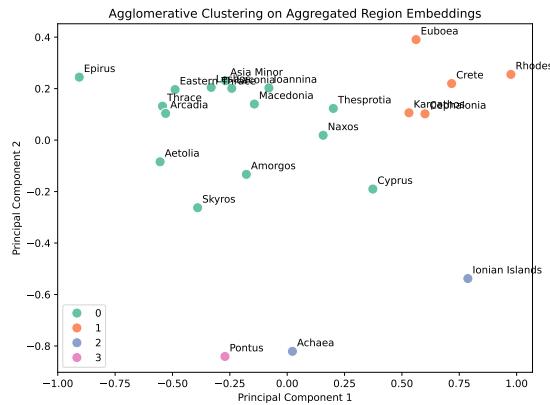


Figure 5: Agglomerative clustering using normalized data

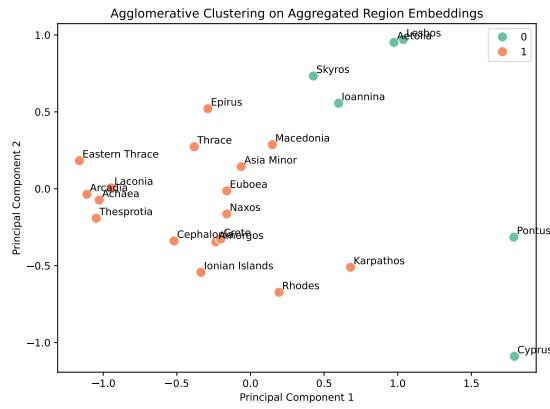


Figure 6: Agglomerative clustering using original dialectal data

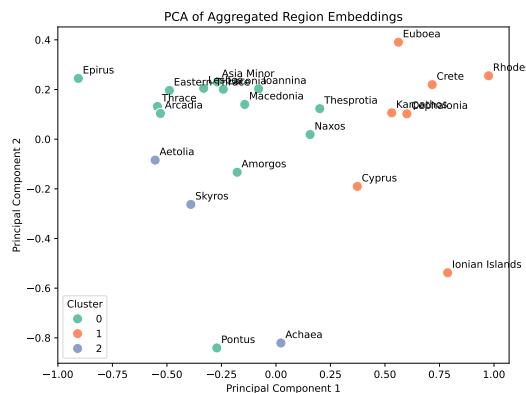


Figure 7: K-means clustering for 3 clusters using normalized data

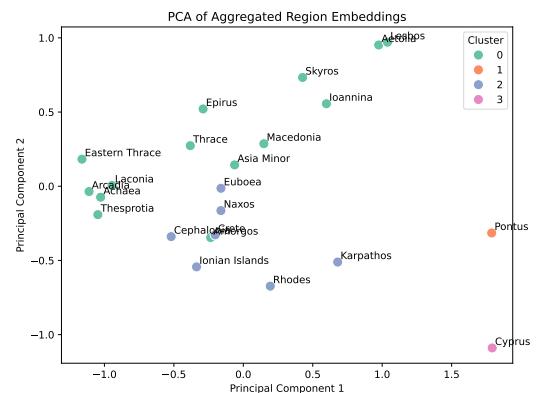


Figure 10: K-means clustering for 4 clusters using original dialectal data

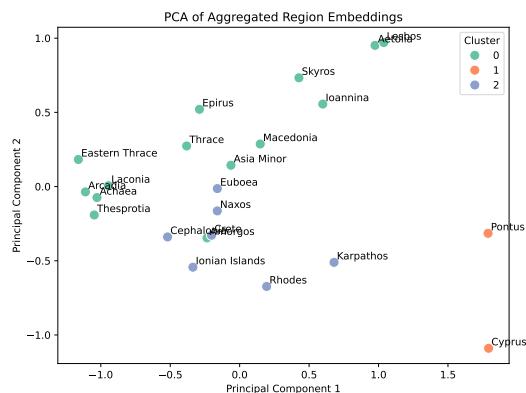


Figure 8: K-means clustering for 3 clusters using original dialectal data

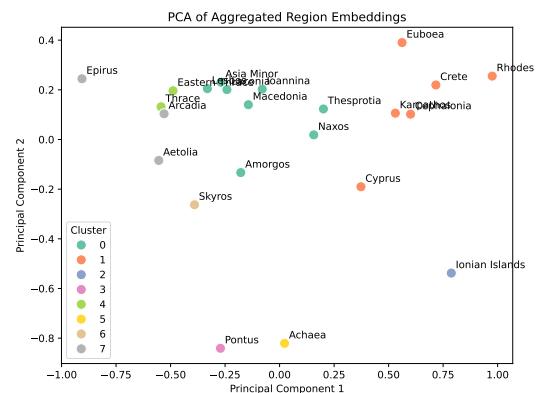


Figure 11: K-means clustering for 8 clusters using normalized data

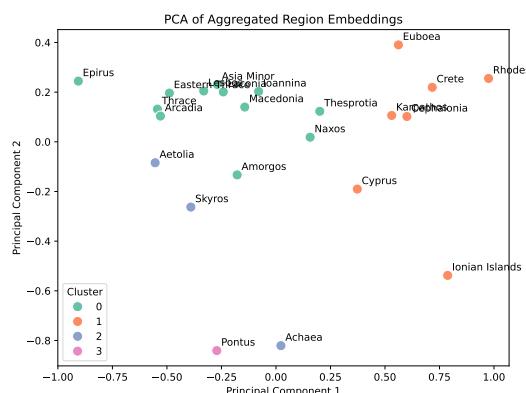


Figure 9: K-means clustering for 4 clusters using normalized data

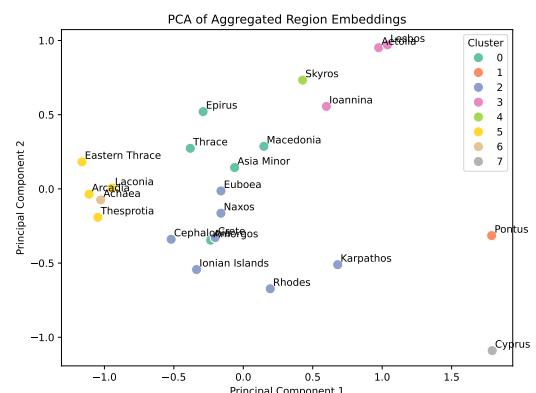


Figure 12: K-means clustering for 8 clusters using original dialectal data

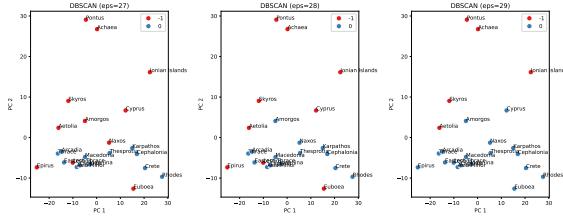


Figure 13: DBSCAN clustering with various values of  $\text{eps}$  using normalized data

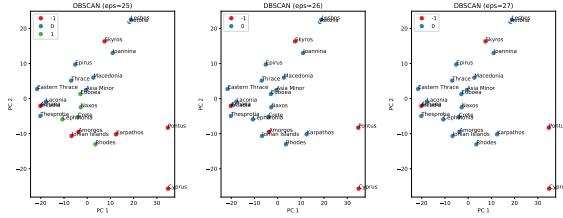


Figure 14: DBSCAN clustering with various values of  $\text{eps}$  using original dialectal data

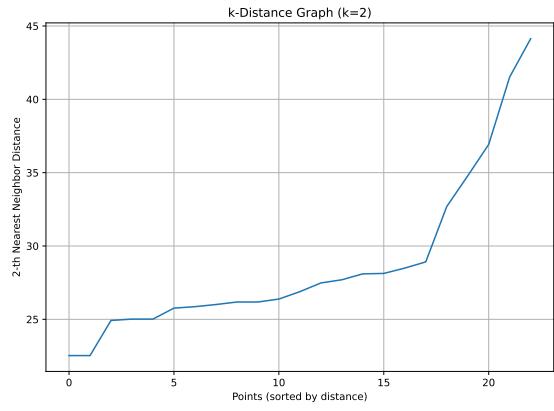


Figure 17: DBSCAN distance graph for finding the optimal  $\text{eps}$  parameter through the elbow method using normalized data

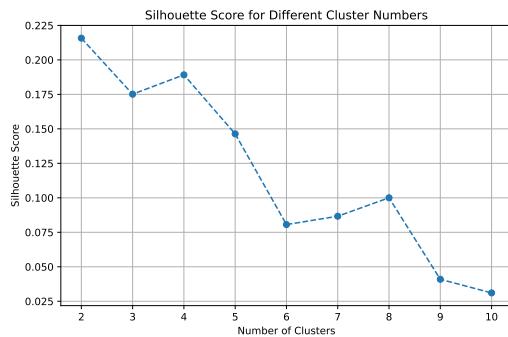


Figure 15: K-means silhouette score by  $k$  to determine optimal number of clusters using normalized data

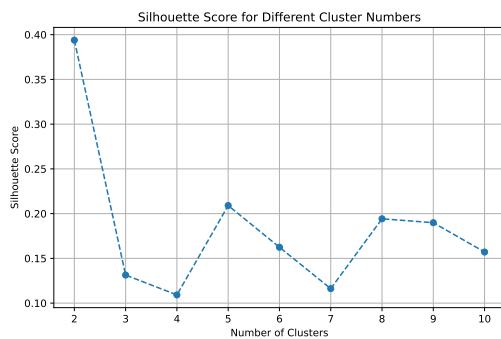


Figure 16: K-means silhouette score by  $k$  to determine optimal number of clusters using original dialectal data

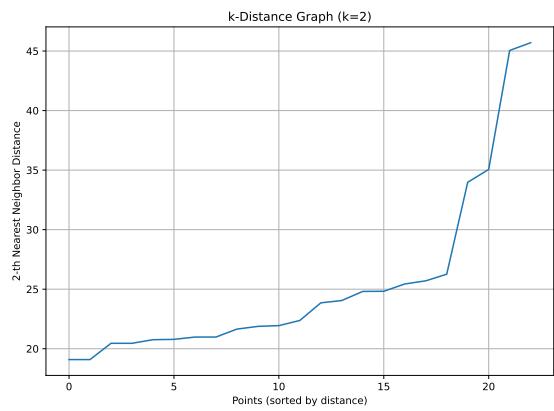


Figure 18: DBSCAN distance graph for finding the optimal  $\text{eps}$  parameter through the elbow method using original dialectal data

## H Detailed Results of Downstream Tasks

| Model          | precision | recall | f1-score | support | Model          | precision | recall | f1-score | support |
|----------------|-----------|--------|----------|---------|----------------|-----------|--------|----------|---------|
| Epirus         | 0.17      | 0.17   | 0.17     | 23      | Epirus         | 0.08      | 0.09   | 0.09     | 23      |
| Aetolia        | 0.38      | 0.58   | 0.46     | 24      | Aetolia        | 0.16      | 0.12   | 0.14     | 24      |
| Amorgos        | 0.13      | 0.18   | 0.15     | 22      | Amorgos        | 0.16      | 0.10   | 0.12     | 29      |
| Eastern Thrace | 0.16      | 0.21   | 0.18     | 24      | Eastern Thrace | 0.14      | 0.14   | 0.14     | 22      |
| Arcadia        | 0.20      | 0.16   | 0.18     | 31      | Arcadia        | 0.10      | 0.07   | 0.08     | 28      |
| Achaea         | 0.39      | 0.22   | 0.28     | 32      | Achaea         | 0.13      | 0.07   | 0.10     | 27      |
| Ionian Islands | 0.35      | 0.65   | 0.45     | 23      | Ionian Islands | 0.24      | 0.33   | 0.28     | 30      |
| Euboea         | 0.06      | 0.05   | 0.05     | 20      | Euboea         | 0.14      | 0.12   | 0.13     | 24      |
| Thesprotia     | 0.05      | 0.05   | 0.05     | 22      | Thesprotia     | 0.13      | 0.17   | 0.15     | 24      |
| Thrace         | 0.25      | 0.16   | 0.20     | 25      | Thrace         | 0.16      | 0.10   | 0.12     | 31      |
| Ioannina       | 0.29      | 0.21   | 0.24     | 29      | Ioannina       | 0.08      | 0.06   | 0.07     | 32      |
| Karpathos      | 0.40      | 0.29   | 0.33     | 28      | Karpathos      | 0.18      | 0.12   | 0.15     | 24      |
| Cephalonia     | 0.14      | 0.11   | 0.12     | 27      | Corfu          | 0.08      | 0.04   | 0.05     | 27      |
| Crete          | 0.35      | 0.27   | 0.30     | 30      | Crete          | 0.06      | 0.07   | 0.07     | 27      |
| Cyprus         | 0.72      | 0.75   | 0.73     | 24      | Cyprus         | 0.04      | 0.06   | 0.05     | 18      |
| Lesbos         | 0.42      | 0.62   | 0.50     | 24      | Lesbos         | 0.32      | 0.43   | 0.37     | 23      |
| Laconia        | 0.12      | 0.07   | 0.09     | 27      | Laconia        | 0.07      | 0.04   | 0.05     | 24      |
| Macedonia      | 0.37      | 0.26   | 0.30     | 27      | Macedonia      | 0.00      | 0.00   | 0.00     | 20      |
| Asia Minor     | 0.00      | 0.00   | 0.00     | 18      | Asia Minor     | 0.04      | 0.05   | 0.04     | 22      |
| Naxos          | 0.31      | 0.46   | 0.37     | 24      | Naxos          | 0.00      | 0.00   | 0.00     | 19      |
| Pontus         | 0.75      | 0.79   | 0.77     | 19      | Pontus         | 0.24      | 0.30   | 0.26     | 30      |
| Rhodes         | 0.26      | 0.23   | 0.24     | 22      | Rhodes         | 0.15      | 0.23   | 0.18     | 22      |
| Skyros         | 0.45      | 0.60   | 0.51     | 30      | Skyros         | 0.10      | 0.16   | 0.12     | 25      |
| accuracy       |           |        | 0.31     | 575     | accuracy       |           |        | 0.13     | 575     |
| macro avg      | 0.29      | 0.31   | 0.29     | 575     | macro avg      | 0.12      | 0.13   | 0.12     | 575     |
| weighted avg   | 0.30      | 0.31   | 0.29     | 575     | weighted avg   | 0.13      | 0.13   | 0.12     | 575     |

Table 11: Location classification with logistic regression with dialectal data

Table 12: Location classification with logistic regression using normalized data

| <b>Model</b>   | <b>precision</b> | <b>recall</b> | <b>f1-score</b> | <b>support</b> | <b>Model</b>   | <b>precision</b> | <b>recall</b> | <b>f1-score</b> | <b>support</b> |
|----------------|------------------|---------------|-----------------|----------------|----------------|------------------|---------------|-----------------|----------------|
| Epirus         | 0.09             | 0.09          | 0.09            | 23             | Epirus         | 0.05             | 0.04          | 0.05            | 23             |
| Aetolia        | 0.42             | 0.46          | 0.44            | 24             | Aetolia        | 0.24             | 0.17          | 0.20            | 24             |
| Amorgos        | 0.26             | 0.32          | 0.29            | 22             | Amorgos        | 0.11             | 0.07          | 0.08            | 29             |
| Eastern Thrace | 0.19             | 0.25          | 0.22            | 24             | Eastern Thrace | 0.08             | 0.09          | 0.09            | 22             |
| Arcadia        | 0.11             | 0.10          | 0.10            | 31             | Arcadia        | 0.09             | 0.07          | 0.08            | 28             |
| Achaea         | 0.31             | 0.25          | 0.28            | 32             | Achaea         | 0.26             | 0.19          | 0.22            | 27             |
| Ionian Islands | 0.47             | 0.70          | 0.56            | 23             | Ionian Islands | 0.24             | 0.20          | 0.22            | 30             |
| Euboea         | 0.06             | 0.05          | 0.05            | 20             | Euboea         | 0.15             | 0.17          | 0.16            | 24             |
| Thesprotia     | 0.11             | 0.09          | 0.10            | 22             | Thesprotia     | 0.16             | 0.25          | 0.19            | 24             |
| Thrace         | 0.26             | 0.20          | 0.23            | 25             | Thrace         | 0.05             | 0.03          | 0.04            | 31             |
| Ioannina       | 0.26             | 0.17          | 0.21            | 29             | Ioannina       | 0.11             | 0.06          | 0.08            | 32             |
| Karpathos      | 0.42             | 0.39          | 0.41            | 28             | Karpathos      | 0.19             | 0.17          | 0.18            | 24             |
| Corfu          | 0.25             | 0.22          | 0.24            | 27             | Corfu          | 0.16             | 0.11          | 0.13            | 27             |
| Crete          | 0.36             | 0.33          | 0.34            | 30             | Crete          | 0.04             | 0.04          | 0.04            | 27             |
| Cyprus         | 0.70             | 0.96          | 0.81            | 24             | Cyprus         | 0.06             | 0.06          | 0.06            | 18             |
| Lesbos         | 0.45             | 0.54          | 0.49            | 24             | Lesbos         | 0.32             | 0.39          | 0.35            | 23             |
| Laconia        | 0.10             | 0.07          | 0.09            | 27             | Laconia        | 0.11             | 0.08          | 0.10            | 24             |
| Macedonia      | 0.35             | 0.30          | 0.32            | 27             | Macedonia      | 0.00             | 0.00          | 0.00            | 20             |
| Asia Minor     | 0.20             | 0.11          | 0.14            | 18             | Asia Minor     | 0.00             | 0.00          | 0.00            | 22             |
| Naxos          | 0.44             | 0.58          | 0.50            | 24             | Naxos          | 0.06             | 0.11          | 0.07            | 19             |
| Pontus         | 0.73             | 0.84          | 0.78            | 19             | Pontus         | 0.28             | 0.33          | 0.30            | 30             |
| Rhodes         | 0.28             | 0.32          | 0.30            | 22             | Rhodes         | 0.14             | 0.23          | 0.17            | 22             |
| Skyros         | 0.54             | 0.63          | 0.58            | 30             | Skyros         | 0.12             | 0.16          | 0.14            | 25             |
| accuracy       |                  |               | 0.34            | 575            | accuracy       |                  |               | 0.13            | 575            |
| macro avg      | 0.32             | 0.35          | 0.33            | 575            | macro avg      | 0.13             | 0.13          | 0.13            | 575            |
| weighted avg   | 0.32             | 0.34          | 0.33            | 575            | weighted avg   | 0.13             | 0.13          | 0.13            | 575            |

Table 13: Location classification with SVM using dialectal data

Table 14: Location classification with SVM using normalized data

| <b>Model</b>   | <b>precision</b> | <b>recall</b> | <b>f1-score</b> | <b>support</b> | <b>Model</b>   | <b>precision</b> | <b>recall</b> | <b>f1-score</b> | <b>support</b> |
|----------------|------------------|---------------|-----------------|----------------|----------------|------------------|---------------|-----------------|----------------|
| Epirus         | 0.05             | 0.04          | 0.05            | 23             | Epirus         | 0.06             | 0.09          | 0.07            | 23             |
| Aetolia        | 0.26             | 0.29          | 0.27            | 24             | Aetolia        | 0.18             | 0.12          | 0.15            | 24             |
| Amorgos        | 0.19             | 0.27          | 0.22            | 22             | Amorgos        | 0.08             | 0.07          | 0.08            | 29             |
| Eastern Thrace | 0.14             | 0.21          | 0.17            | 24             | Eastern Thrace | 0.06             | 0.09          | 0.07            | 22             |
| Arcadia        | 0.14             | 0.13          | 0.13            | 31             | Arcadia        | 0.15             | 0.11          | 0.12            | 28             |
| Achaea         | 0.21             | 0.19          | 0.20            | 32             | Achaea         | 0.12             | 0.07          | 0.09            | 27             |
| Ionian Islands | 0.28             | 0.57          | 0.38            | 23             | Ionian Islands | 0.36             | 0.13          | 0.20            | 30             |
| Euboea         | 0.06             | 0.05          | 0.05            | 20             | Euboea         | 0.12             | 0.17          | 0.14            | 24             |
| Thesprotia     | 0.06             | 0.05          | 0.05            | 22             | Thesprotia     | 0.23             | 0.29          | 0.25            | 24             |
| Thrace         | 0.27             | 0.16          | 0.20            | 25             | Thrace         | 0.04             | 0.03          | 0.03            | 31             |
| Ioannina       | 0.13             | 0.07          | 0.09            | 29             | Ioannina       | 0.11             | 0.09          | 0.10            | 32             |
| Karpathos      | 0.38             | 0.21          | 0.27            | 28             | Karpathos      | 0.18             | 0.17          | 0.17            | 24             |
| Corfu          | 0.18             | 0.19          | 0.18            | 27             | Corfu          | 0.04             | 0.04          | 0.04            | 27             |
| Crete          | 0.24             | 0.20          | 0.22            | 30             | Crete          | 0.12             | 0.11          | 0.12            | 27             |
| Cyprus         | 0.53             | 0.71          | 0.61            | 24             | Cyprus         | 0.06             | 0.06          | 0.06            | 18             |
| Lesbos         | 0.38             | 0.46          | 0.42            | 24             | Lesbos         | 0.19             | 0.26          | 0.22            | 23             |
| Laconia        | 0.12             | 0.11          | 0.12            | 27             | Laconia        | 0.00             | 0.00          | 0.00            | 24             |
| Macedonia      | 0.24             | 0.15          | 0.18            | 27             | Macedonia      | 0.06             | 0.05          | 0.05            | 20             |
| Asia Minor     | 0.00             | 0.00          | 0.00            | 18             | Asia Minor     | 0.00             | 0.00          | 0.00            | 22             |
| Naxos          | 0.25             | 0.29          | 0.27            | 24             | Naxos          | 0.06             | 0.11          | 0.07            | 19             |
| Pontus         | 0.57             | 0.68          | 0.62            | 19             | Pontus         | 0.25             | 0.20          | 0.22            | 30             |
| Rhodes         | 0.21             | 0.18          | 0.20            | 22             | Rhodes         | 0.20             | 0.27          | 0.23            | 22             |
| Skyros         | 0.52             | 0.50          | 0.51            | 30             | Skyros         | 0.09             | 0.08          | 0.08            | 25             |
| accuracy       |                  |               | 0.25            | 575            | accuracy       |                  |               | 0.11            | 575            |
| macro avg      | 0.23             | 0.25          | 0.23            | 575            | macro avg      | 0.12             | 0.11          | 0.11            | 575            |
| weighted avg   | 0.24             | 0.25          | 0.23            | 575            | weighted avg   | 0.12             | 0.11          | 0.11            | 575            |

Table 15: Location classification with KNN using dialectal data

Table 16: Location classification with KNN using normalized data

| <b>Model</b>   | <b>precision</b> | <b>recall</b> | <b>f1-score</b> | <b>support</b> | <b>Model</b>   | <b>precision</b> | <b>recall</b> | <b>f1-score</b> | <b>support</b> |
|----------------|------------------|---------------|-----------------|----------------|----------------|------------------|---------------|-----------------|----------------|
| Epirus         | 0.07             | 0.04          | 0.05            | 23             | Epirus         | 0.06             | 0.09          | 0.07            | 23             |
| Aetolia        | 0.33             | 0.71          | 0.45            | 24             | Aetolia        | 0.07             | 0.04          | 0.05            | 24             |
| Amorgos        | 0.08             | 0.14          | 0.10            | 22             | Amorgos        | 0.31             | 0.14          | 0.19            | 29             |
| Eastern Thrace | 0.15             | 0.21          | 0.17            | 24             | Eastern Thrace | 0.15             | 0.14          | 0.14            | 22             |
| Arcadia        | 0.18             | 0.16          | 0.17            | 31             | Arcadia        | 0.04             | 0.04          | 0.04            | 28             |
| Achaea         | 0.48             | 0.38          | 0.42            | 32             | Achaea         | 0.30             | 0.22          | 0.26            | 27             |
| Ionian Islands | 0.24             | 0.22          | 0.23            | 23             | Ionian Islands | 0.24             | 0.30          | 0.27            | 30             |
| Euboea         | 0.00             | 0.00          | 0.00            | 20             | Euboea         | 0.11             | 0.12          | 0.12            | 24             |
| Thesprotia     | 0.13             | 0.14          | 0.13            | 22             | Thesprotia     | 0.18             | 0.17          | 0.17            | 24             |
| Thrace         | 0.43             | 0.24          | 0.31            | 25             | Thrace         | 0.10             | 0.06          | 0.08            | 31             |
| Ioannina       | 0.10             | 0.07          | 0.08            | 29             | Ioannina       | 0.12             | 0.06          | 0.08            | 32             |
| Karpathos      | 0.58             | 0.25          | 0.35            | 28             | Karpathos      | 0.15             | 0.12          | 0.14            | 24             |
| Corfu          | 0.21             | 0.22          | 0.21            | 27             | Corfu          | 0.07             | 0.04          | 0.05            | 27             |
| Crete          | 0.33             | 0.17          | 0.22            | 30             | Crete          | 0.00             | 0.00          | 0.00            | 27             |
| Cyprus         | 0.55             | 0.88          | 0.68            | 24             | Cyprus         | 0.03             | 0.06          | 0.04            | 18             |
| Lesbos         | 0.43             | 0.62          | 0.51            | 24             | Lesbos         | 0.35             | 0.35          | 0.35            | 23             |
| Laconia        | 0.09             | 0.07          | 0.08            | 27             | Laconia        | 0.00             | 0.00          | 0.00            | 24             |
| Macedonia      | 0.11             | 0.04          | 0.06            | 27             | Macedonia      | 0.06             | 0.10          | 0.07            | 20             |
| Asia Minor     | 0.00             | 0.00          | 0.00            | 18             | Asia Minor     | 0.03             | 0.05          | 0.04            | 22             |
| Naxos          | 0.35             | 0.38          | 0.36            | 24             | Naxos          | 0.05             | 0.05          | 0.05            | 19             |
| Pontus         | 0.40             | 0.74          | 0.52            | 19             | Pontus         | 0.27             | 0.40          | 0.32            | 30             |
| Rhodes         | 0.19             | 0.23          | 0.21            | 22             | Rhodes         | 0.17             | 0.32          | 0.22            | 22             |
| Skyros         | 0.43             | 0.67          | 0.53            | 30             | Skyros         | 0.12             | 0.16          | 0.14            | 25             |
| accuracy       |                  |               | 0.29            | 575            | accuracy       |                  |               | 0.13            | 575            |
| macro avg      | 0.25             | 0.28          | 0.25            | 575            | macro avg      | 0.13             | 0.13          | 0.13            | 575            |
| weighted avg   | 0.26             | 0.29          | 0.26            | 575            | weighted avg   | 0.13             | 0.13          | 0.13            | 575            |

Table 17: Location classification with Random Forest using dialectal data

Table 18: Location classification with Random Forest using normalized data

| <b>Model</b>               | <b>lat MAE</b> | <b>lon MAE</b> | <b>lat MSE</b> | <b>lon MSE</b> |
|----------------------------|----------------|----------------|----------------|----------------|
| ElasticNet                 | <b>1.37</b>    | <b>2.77</b>    | <b>2.94</b>    | <b>14.31</b>   |
| K Nearest Neighbors        | 1.47           | 3.13           | 3.34           | 16.65          |
| Linear Regression          | 1.38           | 2.80           | 3.00           | 14.70          |
| Random Forest              | 1.43           | 2.82           | 3.16           | 14.63          |
| Extremely Randomized Trees | 1.43           | 2.84           | 3.15           | 14.68          |

Table 19: Geolocation regression using dialectal data

| <b>Model</b>               | <b>lat MAE</b> | <b>lon MAE</b> | <b>lat MSE</b> | <b>lon MSE</b> |
|----------------------------|----------------|----------------|----------------|----------------|
| ElasticNet                 | 1.51           | 2.98           | 3.40           | 17.68          |
| K Nearest Neighbors        | 1.55           | 2.96           | 3.57           | 17.47          |
| Linear Regression          | 1.54           | 3.08           | 3.57           | 18.44          |
| Random Forest              | 1.51           | 2.90           | 3.42           | 17.18          |
| Extremely Randomized Trees | 1.52           | 2.92           | 3.47           | 17.40          |
| GreekBERT                  | <b>1.35</b>    | <b>1.83</b>    | <b>2.76</b>    | <b>5.57</b>    |

Table 20: Geolocation regression using normalized data

## I GreekBERT Fine-Tuning Hyperparameters

We add a 30% dropout and a single linear layer as a regressor on top of the Greek BERT model and train it on 80% of our data, keeping 10% as a validation set for early stopping after 2 epochs of non-improvement, for a maximum of 15 epochs. We then test it on the remaining 10% of our data. We use mean squared error as the loss function, AdamW as the optimizer,  $2 \times 10^{-5}$  as the learning rate and a batch size of 32.