The Curious Case of Logistic Regression for Italian Languages and Dialects Identification

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Abstract

Automatic Language Identification represents an important task for improving many real-world applications such as opinion mining and machine translation. In the case of closely-related languages such as regional dialects, this task is often challenging. In this paper, we propose an extensive evaluation of different approaches for the identification of Italian dialects and languages, spanning from classical machine learning models to more complex neural architectures and state-of-the-art pre-trained language models. Surprisingly, shallow machine learning models managed to outperform huge pre-trained language models in this specific task. This work was developed in the context of the Identification of Languages and Dialects of Italy (ITDI) task organized at VarDial 2022 Evaluation Campaign. Our best submission managed to achieve a weighted $F_1$-score of 0.6880, ranking 5th out of 9 final submissions.

1 Introduction

Dialect classification represents a key task in the improvement of many other downstream tasks such as opinion mining and machine translation, where the enrichment of text with geographical information can potentially result in improved performances for real-world applications (Zampieri et al., 2020).

As a result, the interest in the study of language variation has been steadily growing in the last few years, as highlighted by the increasing number of publications and events related to the topic (Zampieri et al., 2014, 2015; Malmasi et al., 2016; Zampieri et al., 2017, 2018, 2019; Gaman et al., 2020; Chakravarthi et al., 2021). However, little has been done so far by researchers in the context of automatic dialect and language recognition for the Italian language.

In this context, the Identification of Languages and Dialects of Italy (ITDI) task of VarDial 2022 Evaluation Campaign (Aepli et al., 2022) aims to bridge this gap, facilitating the development of models capable of properly classifying 11 regional languages and dialects from Italy’s mainland and islands. Figure 1 shows the geographical origin of these different dialects and languages.

In this paper, we present the results of an extensive evaluation of three different approaches for the automatic identification of the given dialects. After an introductory literature review (§2), we proceed with a more in-depth discussion on the details of the ITDI task and the dataset provided by the organizers (§3). Then, we introduce the proposed architectures (§4) and the experimental results for each one of them (§5). We also provide some additional analysis of the models on classification errors and feature space visualization (§6). Finally, we include some concluding remarks on the shared tasks and possible limitations and routes for improvement of our work (§7).

For a more complete and accurate map, refer to https://en.wikipedia.org/wiki/Languages_of_Italy.
2 Related Works

Dialect identification represents a well-known task in the literature, for which the first contributions can be traced back to more than fifty years ago (Mustonen, 1965). An extensive and complete review of the field can be found in (Jauhiainen et al., 2019). However, language identification still represents a non-trivial task in the case of closely-related languages and dialects.

Although deep neural models nowadays yield state of the art performances in many NLP tasks, shallow machine learning models have shown to be still highly competitive in discriminating between similar languages. Some examples are Linear SVM and Naïve Bayes classifiers (Ceolin, 2021; Çöltekin, 2020) and Logistic Regression (Bhargava et al., 2015; Ács et al., 2015).

Also the use of Convolutional Neural Networks is still popular in this type of task. In particular, CNN-based approaches achieved competitive results in both VarDial 2019 Evaluation Campaign (Tudoreanu, 2019) and VarDial 2020 Evaluation Campaign (Rebeja and Cristea, 2020).

The introduction of transformers (Vaswani et al., 2017) has represented a breakthrough in many NLP tasks, and language identification is no exception. Models based on this architecture achieved state-of-the-art performance in many practical applications. A recent example is again VarDial 2020 Evaluation Campaign, where the use of a fine-tuned version of BERT previously trained on three publicly available Romanian corpora (Zaharia et al., 2020) reached a weighted $F_1$ score of 96.25% on the MOCRoco dataset (Butnaru and Ionescu, 2019) in the Romanian vs Moldavian identification task.

However, the literature regarding automatic Italian languages and dialects identification is still relatively underdeveloped. Some recent work has been done to encourage the study of the diachronic evolution of Italian language and the differences between its dialects (Zugarini et al., 2020), but no prior work has focused specifically on contemporary Italian dialects identification.

3 Task and Data Description

3.1 ITDI

ITDI is one of the three tasks proposed as part of the VarDial 2022 Evaluation Campaign.

The language varieties evaluated in this task are 11, both from Northern Italy (Piedmontese, Venetian, Emilian-Romagnol, Ligurian, Friulian, Ladin, and Lombard), Southern Italy (Neapolitan and Tarantino) and Islands (Sardinian and Sicilian). In the following chapters, varieties’ names will be abbreviated coherently with (Aepli et al., 2022).

This is the first edition of the task. The task is closed, therefore, participants are not allowed to use external data to train their models (except for off-the-shelf pre-trained language models).

The training dataset is provided by the organizers and consists of 265 016 selected Wikipedia articles from March 1st 2022 dumps, comprehensive of all the 11 varieties evaluated in the task. The development set consists of 6799 annotated sentences that cover only 7 out of the 11 varieties evaluated in the shared tasks (there are no development samples for Emilian, Neapolitan, Ladin, and Tarantino). The test set, on the other hand, consists of 11 090 samples, and covers only 8 out of the 11 varieties (Piedmontese, Sicilian and Sardinian are not represented). The composition of the test set was disclosed only after the end of the competition.

3.2 Data Exploration

Since the training data don’t come from a well-known documented dataset, a preliminary exploration has been initially conducted to gain useful insight about them. This investigation highlighted a huge imbalance between classes as shown in Figure 2, since the 3 most represented dialects (Venetian, Piedmontese and Lombard) account for almost three quarters of the articles in the training data. On the other hand, other dialects (such as Friulian, Emilian-Romagnol, and Ligurian) are heavily under-represented.

Hence, imbalanced data seems to represent a major challenge and should be addressed during the development and evaluation of the model.

Figure 2: Percentages of Wikipedia articles per variety.
3.3 Pre-Processing of the Wikipedia Dumps

The training data is provided in the form of raw Wikipedia dumps and, as highlighted by the organizers, a careful pre-processing is an important part of the task. In this section, we describe how we extracted and cleaned samples from the raw Wikipedia dumps.

**Document extraction** The extraction of Wikipedia documents and an initial pre-processing step is performed using WikiExtractor (Attardi, 2015), a Python script that extracts and cleans text from Wikipedia database dumps. The use of this particular tool for extraction was suggested by the organizers of the shared task. However, a careful qualitative analysis of the resulting text samples pointed out the need for more fine-grained processing of training samples.

**Document cleaning** Firstly, we remove all the HTML tags (e.g., `<br>`, `&`, etc.) and Wikipedia meta information (e.g., contributors, timestamps and comments) that were not successfully filtered out by WikiExtractor. Then, we observe that most of the documents of length < 50 characters are not valuable samples, as they come from documents for which WikiExtractor failed to extract any text at all or from pages that contain simple and repetitive name entity definitions (e.g., small towns or years articles). Hence, we trim them from the training dataset. Moreover, we observe that the training set contains duplicate documents (e.g., Web domain pages in Venetian Wikipedia). Therefore, we remove all the duplicate documents from the dataset.

**Sentence splitting** Finally, since the task evaluates dialect classification at sentence level, we split all the documents into sentences using the Italian spaCy tokenizer (Honnibal and Montani, 2017). After the splitting, a further filtering is applied to the sentences to trim a huge set of almost-identical sentences from the training data (e.g., sentences about municipalities, cities or years that occur thousand of times and differ only in the entity name). Moreover, we fix some transcription mismatches between training and validation samples (e.g., Venetian Wikipedia articles use the letter "ł" to transcribe particular phonemes, which is, on the other hand, transcribed as a standard "l" in the validation samples).

**Pre-processing results** The exact number of samples after each pre-processing step is shown in Table 1, while a representation of the distribution of the input sentences over all the 11 dialects can be found in Figure 3. It can be observed from the latter that the distribution of training samples is slightly more uniform compared to the initial Wikipedia document distribution. Nonetheless, the substantial class imbalance between different languages and dialects persists.

![Figure 3: Number of sentences in the training set for each of the eleven dialects included in the task.](image)

Table 1: Number of training samples after each pre-processing step.

| Pre-processing step        | # samples |
|----------------------------|-----------|
| Original documents         | 265 016   |
| remove length < 50         | 244 688   |
| remove duplicates          | 218 670   |
| sentence split             | 698 837   |
| sentence cleaning          | 382 859   |

4 Methods

4.1 Linear Models

Linear models are still a widely used tool in the context of automatic language identification. We experiment with three different models, namely Linear Support Vector Machines (SVM), Naïve Bayes classifiers (NB) and Logistic Regression (LR). The models are trained on scaled word-level TF-IDF feature vectors. We also experiment with models trained on character-level n-grams TF-IDF, word-level n-grams TF-IDF, or other type of text embedding (e.g., hashing vectorizers) and scaling techniques. Dimensionality-reduction techniques to reduce the initial embedding dimensions are also investigated. All the models that we use in these experiments are off-the-shelf models from the Python library scikit-learn (Pedregosa et al., 2011).
4.2 Convolutional Neural Networks

Convolutional Neural Networks (CNN) are a powerful modular approach for text classification (Zhang et al., 2015). We implemented both word-based and character-based networks. In this section, we introduce the design of the character-level network. Besides replacing an alphabet of characters with a vocabulary of words, the word-level CNN approach is identical. The encoding is performed extracting an alphabet of size $m$ from the training data. Each input sentence is transformed into a sequence of $m$-sized vectors with fixed length $l_0$. Any character exceeding length $l_0$ is ignored, and any character that is not in the alphabet, including blank characters, is encoded as an all-zero vector. In our particular dataset, the alphabet extracted from the training set consists of $m = 989$ characters. We set $l_0 = 60$ and add 0 padding if the sequence is shorter than 60 characters.

Table 7 describes in detail the CNN architecture. Both character-level and word-level networks are 3 layers deep, with 2 convolutional layers and 1 fully-connected layer. ReLU function is then used as an additional step on top of convolution. We choose max-pooling to represent features map to Pooled Feature Map, which helps reducing the number of parameters and prevent overfitting. In the fully-connected step, we combine all input features resulting from the last hidden layer to predict the classes using a softmax function.

4.3 Transformers

The use of transformer-based models has been proved effective even in the context of language identification. In particular, the fine-tuning of large pre-trained language models such as BERT (Devlin et al., 2019) yielded competitive performances in the previous iteration of VarDial Evaluation Campaign (Zaharia et al., 2020). Following this line of work, we experiment with the fine-tuning of six HuggingFace BERT models:

- AlBERTo (Polignano et al., 2019), an Italian uncased BERT$_{\text{BASE}}$ model pre-trained on Italian tweets.
- dbmdz-cased/uncased (Schweter, 2020), an Italian BERT$_{\text{BASE}}$ model pre-trained on Italian Wikipedia dump and various texts from the OPUS corpora.
- dbmdz-xxl-cased (Schweter, 2020), an Italian BERT$_{\text{LARGE}}$ model pre-trained on Italian Wikipedia dump and various texts from the OPUS corpora and OSCAR corpus.
- mrm8488-bert (Romero, 2020), a dbmdz-cased with an additional fine-tuning on Italian SQuAD for Q&A, to measure the impact of additional tuning on downstream tasks.
- multilingual BERT$_{\text{BASE}}$ (Devlin et al., 2019), pre-trained on a corpora of 102 languages.

For all the encoders, a linear classifier is added on top of the CLS token, and the resulting model is then fine-tuned for two epochs on the identification task. A non-extensive hyper-parameter tuning is performed on the best-scoring model, re-training it with both frozen and non-frozen embeddings and with variable maximum sequence length. The use of class weights to counter class imbalance, as well as different classifier layers, are also investigated.

5 Results and Discussion

5.1 Linear Models

Initially designed and implemented as baseline references, linear models ended up achieving the greatest performances among all the investigated methods. Table 2 shows the results for this category of approaches.

For conciseness, we only report validation scores for models trained on word-level TF-IDF embeddings scaled to zero mean and unit variance. Other embedding (hashing vectorization) and scaling (no scaling, robust scaling) techniques don’t show any performance improvement. Projecting the original embeddings to a lower-dimensional features space with Principal Component Analysis also results in an overall performance decay.

Among the implemented models (SVM, NB and LR), LR is the one that achieves the best performance, with a F$\text{1}$-micro score of 0.8957. Thus, we proceed with an extensive hyper-parameter search for this specific method.

| Model           | Embedding | F$\text{1}$-micro |
|-----------------|-----------|-------------------|
| Linear SVM      | tf-idf    | 0.8308            |
| Naïve Bayes     | tf-idf    | 0.8467            |
| Logistic Regression | tf-idf    | 0.8957            |
| + SAG solver    | tf-idf    | 0.9295            |
| + class weights | tf-idf    | **0.9445**        |
| LR ensemble     | tf-idf    | 0.9424            |

Table 2: Linear model evaluation on the validation set.
We find that the use of SAG solver (Schmidt et al., 2017) and class weights (to counter the training set class imbalance, defined using cross-validation) further increases the validation score, reaching a final $F_1$-micro of 0.9445. Table 3 shows a more detailed evaluation of the model on single dialects. Finally, we implement an ensemble of LR models trained with different class weights (inversely proportional to class frequency and cross-validated) and random seeds. However, the ensemble doesn’t improve the validation score.

| Dialect | Precision | Recall | $F_1$ | Support |
|---------|-----------|--------|-------|---------|
| PMS     | 0.95      | 0.99   | 0.97  | 1191    |
| FUR     | 0.99      | 0.99   | 0.99  | 676     |
| LIJ     | 0.96      | 0.99   | 0.98  | 617     |
| LMO     | 0.92      | 0.93   | 0.92  | 1231    |
| SCN     | 0.96      | 0.96   | 0.96  | 1371    |
| VEC     | 0.95      | 0.89   | 0.92  | 1236    |
| SC      | 0.93      | 0.85   | 0.89  | 477     |

Table 3: Best LR model evaluation on single validation dialects. The last two rows report the overall model accuracy and weighted average of each metric.

We speculate that the great performances achieved by this method depend on the consistent linguistic variety between the evaluated Italian dialects and languages, which allows for a neat separation of the different classes in the feature space induced by TF-IDF. Moreover, an important advantage of LR model might be, surprisingly, its simplicity. The number of parameters learned by the model is relatively small (~5 million) compared to other investigated models (BERT has 110 million parameters). This might prevent the model from overfitting the training data and improve its ability to generalize to out-domain sentences.

On the other hand, the LR approach shows some intrinsic limitations that are difficult to overcome, namely the impossibility of handling out-of-vocabulary words (OOV) and the missing dialects in the validation set, which might lead to an overfit of the validation dialects.

5.2 CNN

The details of implemented models are provided in Appendix A section with the table 7. By implementing different sets of hyper-parameter, we aim to find a better model architecture and training regime for classifier tasks. Several hyper-parameters, including learning rate, dropout, kernel sizes, batch sizes, embedding size, are taken into consideration in our experiment.

Table 4 shows the classification results of two CNN models over a different number of epochs. The best performance is achieved from the CNN model tokenized at character-level trained over 20 epochs. In general, there is no significant difference between CNN char-level and word-level implementation. On the other hand, the training for the word-level implementation is remarkably more time-expensive compared to the same setting running on the CNN char-level. The computational cost difference between the two approaches might be explained by their different vocabulary size. The vocabulary size of CNN word-level models and CNN character-level models are shown in the table 7 and are respectively 989 and 788, 197 tokens.

The best CNN model achieves a $F_1$-micro score of 0.8605 on the validation data, showing a significant performance gap compared to linear models results mentioned in §5.1.

We identify two main reasons why Convolutional Neural Network could not perform better than other linear classifiers. Firstly, the noncompetitive result of CNN might be the consequences of how text is embedded. We encode text in character-level/word-level with different embedding sizes. However, a single character, i.e., 1-gram, is the only way to encode the text. Meanwhile, in linear models we encoded texts with different configurations, including word levels, character levels and characters within the boundary of word level. Secondly, CNN might be more complicated than classifier methods to handle our dataset. In general, a powerful model tends to treat simple problems with complicated architecture. This leads to the over-fitting issue, which indicates that our model is too complex for the problem that it is solving. Consequently, the model resulting from CNN performs poorly on the unseen data.

| Encoding  | Epochs | $F_1$-micro |
|-----------|--------|-------------|
| char-level| 5      | 0.8421      |
| char-level| 10     | 0.8555      |
| char-level| 20     | 0.8605      |
| word-level| 5      | 0.8299      |
| word-level| 10     | 0.8513      |

Table 4: CNN models evaluation on the validation set.
5.3 Transformers
Table 5 shows the evaluation for the 6 different pre-trained BERT (Devlin et al., 2019) investigated. In general, all models yield similar performances, fluctuating from approximately 0.87 to 0.89 of F1-micro score, while there is a significant difference in the training time between dbmdz-xxl-cased and the others. However, dbmdz-xxl-cased achieves the best identification performance, with an F1-micro score of 89.07%.

In the second phase, we perform a more detailed investigation on the best-scoring model built on dbmdz-xxl-cased. Table 8 in Appendix B shows models evaluation with several set of hyperparameters. Class weights, sequence max lengths, and freezing embeddings are investigated.

Concerning class weights, both validation weights used in LR and proportionally-inverse weight are investigated to reduce the class imbalance issue. Yet, both weights slightly decrease model performances. In particular, class weights result in a score decrease of 0.43%.

Then, we observe that freezing the CLS embeddings for the model, i.e. training only the linear classifier and not the stacked encoding layers during the fine-tuning, leads to a significant decrease in the validation score. We hypothesize that, due to the significant difference between Italian language and its dialects, BERT model cannot be used as feature extractor without an additional fine-tuning.

Finally, we observe that increasing the max length of each sentence from 50 to 70 improved the identification score. Setting a sequence’s maximum length is important because it decides how much information the model can extract. However, an increased training cost is the direct drawback of this approach. Table 8 shows that the training time increased more than 35%, from 56 minutes to 76 minutes, with the same setup.

The visualization of CLS embeddings (described in §6.2) pushed us to further experiment with different classifiers trained on top of them. However, none of the investigated methods (MLPs, bagging and boosting) achieved noticeable improvements on the default linear classifier.

| Team | Model  | Accuracy | F1-micro |
|------|--------|----------|----------|
| SUKI | -      | 0.9053   | 0.9007   |
| Phlyers | -    | 0.6817   | 0.6943   |
| ETHZ | LR     | 0.6718   | 0.6880   |
|      | BERT   | 0.5759   | 0.5760   |
|      | LR**   | 0.6952   | 0.7058   |

Table 6: Final ITDI shared leaderboard.

5.4 Shared Task Results
The final results of ITDI task are shown in Table 6. In our case, the best submission ranked 5th out of 9 total submissions with an F1-micro score of 0.6880. This submission was produced using the best LR model from §5.1, trained on both training and validation data together. However, this solution could have been further improved with a better choice of class weights. Inspired by (King and Zeng, 2001), we defined alternative weights as \( w_c = \tau/\bar{y} \), where \( \tau \) is the fraction of class \( c \) in the population (here supposed uniform across all the dialects), and \( \bar{y} \) is the fraction in the training sample. With this choice of weights, our late submission (**, not ranked) achieved an F1-micro of 0.7058. Predictions from the best-performing BERT model (described in §5.3) achieved an F1-micro of 0.5760. The submission produced with the CNN was withdraw from the competition because of a minor bug in the prediction shuffling. Detailed identification scores for every class are included in Appendix D.

For all the models, a huge gap between validation and test score can be clearly observed. This discrepancy can be mainly attributed to two dialects that were not included in the validation set but were evaluated in the test, namely Tarantino and Ladin.

We speculate that Ladin, in particular, caused the greatest decay in our final score. Its low recall, together with the low accuracy registered for Venetian and Lombard, points out a degenerate behaviour of the classifier, which seems to classify most of Ladin samples as one of the other two dialects, hence lowering all the respective F1 scores. On the other hand, Tarantino was probably intrinsically difficult to discriminate, as all the teams achieved poor performances on its identification.
6  Analysis

6.1  Error Analysis

In this section, we present a more fine-grained analysis of the incorrect predictions for our best-performing model, Logistic Regression.

Firstly, we investigate the most confounded dialects and languages on the development set. The resulting confusion matrix is reported in Figure 4. It is possible to observe how the greatest source of confusion for the models is represented by two pairs of dialect, Lombard-Venetian and Sardinian-Sicilian. In fact, 6.5% of Venetian sentences (81 sentences) are classified as Lombard, and 7.9% of Sardinian sentences (38 sentences) are labeled as Sicilian. This, together with the trade-off between the performances on the exact same two pairs of dialects (observed during the fine-tuning of the model), corroborates the hypothesis of an intrinsic difficulty in the discrimination between the two pairs of dialects. We speculate that this phenomenon might origin in a consistent number of shared lexical features, mainly due to geographical and cultural factors. Furthermore, this behaviour is observed also for CNN and BERT models (as shown in the confusion matrices included in Appendix E), confirming its model-agnostic nature.

In Multinomial Logistic Regression, for each class $y_k$ the model computes a log-odds ratio $\log \frac{p}{1-p}$ (also known as logit$(p)$) of the probability $p$ that sample $X$ belongs to class $y_k$ as

$$\text{logit}_{y_k}(p) = \beta_{k,0} + \sum_{i=1}^{N} \beta_{k,i} X_i$$

where $X$ is the input vector and $\beta$ is the learned coefficients vector. Hence, the contribution $\psi_k$ of each feature $X_i$ to the odds that the sample $X$ is classified as $y_k$ equals to

$$\psi_k(X_i) = e^{\beta_i X_i}$$

In our analysis, we extract for each wrongly classified sample all the the confounding features with a contribution to the wrong class $\psi_{\text{wrong}} > 1.2$, that is all the features that increased the odds of the wrong class by more than 20%.

As expected, most of these features are either Italian words (for example no, perché, non, con, chi) or words shared between the confounded dialects (for example cossa, lu, me, vegnir). In particular, we further investigate the distribution of these words in the training and validation dataset. The result of this analysis shows a considerable discrepancy in the distributions for most of the studied features, reported for some of them in Figure 5.

We therefore speculate that the difference across in-domain and out-domain vocabulary distribution is one of the main issues that cause misclassification of the model.
6.2 Visualization

To gain additional insights on the different embedding techniques used by the investigated methods, we try to visualize their respective high-dimensional feature spaces. In particular, we exploit two well-known dimensionality-reduction techniques, Principal Component Analysis (Pearson, 1901) and t-distributed Stochastic Neighbor Embedding (t-SNE) (van der Maaten and Hinton, 2008), to obtain 2-dimensional projections of the validation embeddings.

**Technique**   PCA is initially used to project the TF-IDF embeddings to a 1000-dimensional space (preserving 68.71% of the information). Then, t-SNE is applied to these projection to obtain a final two-dimensional visualization. The combination of PCA and t-SNE obtained slightly better visual results compared to their independent application. In the case of CNN and BERT the PCA step is omitted, as the original embeddings (linear layer input for CNN and CLS token for BERT, both extracted from fine-tuned instances of the respective best models) have already a limited number of dimensions 7728 and 768 respectively. The results of these visualizations are presented in Figure 6.

**Results**   In TF-IDF visualization, it’s possible to identify one cluster for each dialect (with the exception of Sardinian). The clusters are not well-separated when compared to BERT visualization, but this might be due to the loss of information introduced in the projection from an extremely high-dimensional space (3 orders of magnitude higher than BERT) to the 2-dimensional space.

CNN embeddings are on the other hand chaotic. It is possible to identify some clusters in the projected space, but they are not as clear as for the other two models.

The visualization for BERT embeddings is, on the other hand, particularly meaningful. The clusters for different dialects are clearly outlined. Moreover, it’s interesting to observe how the most confused dialects from §6.1 (Lombard-Venetian and Sardinian-Sicilian) effectively show overlapping embeddings in the hyperspace.

7 Conclusion

This paper presented the findings of our team at the Vardial 2022 ITDI shared tasks. The Logistic Regression model achieved the best results, outperforming the other two models and ranking within the top 5 submissions. Although CNN and BERT approaches have not yielded remarkable results, the experiments produced valuable insights. In particular, we observed no notable difference in the model performance of character-based and word-based CNN, of which the vast vocabulary size is more costly in terms of training time. On the other hand, BERT models performed weakly in this cross-domain language identification task, generalising less than linear models.

In the future, models’ performances could be increased by calibrating different class weights on a validation set comprehensive of all the dialects and languages, and also a more extensive hyperparameters fine-tuning for the neural models could be carried out. This could, eventually, increase the cross-domain adaptability of our models.
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Additional Resources

The code from our experiments can be found on GitHub (2), while a deployed demo of our model can be found on Herokuapp (3).

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**Appendix A  CNN Model Summary**

In this Appendix section, we provide a more detailed insight on the CNN model structure. Table 7 reports the summary of both character-level and word-level networks.

| Tokenization | CNN Model Summary |
|--------------|-------------------|
| **Character level** | |
| (embeddings): Embedding(989, 512) | |
| (conv2d): Conv2d(1, 16, kernel_size=(3, 3), stride=(2, 1), padding=(1, 0)) | |
| (max_pool2d): MaxPool2d(kernel_size=(6, 12), stride=(2, 1), padding=(1, 0), dilation=1, ceil_mode=False) | |
| (conv2d_2): Conv2d(16, 16, kernel_size=(6, 6), stride=(2, 1), padding=(1, 0)) | |
| (max_pool2d_2): MaxPool2d(kernel_size=(6, 12), stride=(2, 1), padding=(1, 0), dilation=1, ceil_mode=False) | |
| (linear): Linear(in_features=7728, out_features=12, bias=True) | |
| **Word level** | |
| (embeddings): Embedding(788197, 512) | |
| (conv2d): Conv2d(1, 16, kernel_size=(3, 3), stride=(2, 1), padding=(1, 0)) | |
| (max_pool2d): MaxPool2d(kernel_size=(6, 12), stride=(2, 1), padding=(1, 0), dilation=1, ceil_mode=False) | |
| (conv2d_2): Conv2d(16, 16, kernel_size=(6, 6), stride=(2, 1), padding=(1, 0)) | |
| (max_pool2d_2): MaxPool2d(kernel_size=(6, 12), stride=(2, 1), padding=(1, 0), dilation=1, ceil_mode=False) | |
| (linear): Linear(in_features=7728, out_features=12, bias=True) | |

Table 7: CNN Model Summary

**Appendix B  Evaluation of BERT dbmdz-xxl-cased**

In this Appendix section, we provide the evaluation results for the best-scoring BERT model, dbmdz-xxl-case, with several set of hyper-parameters. Results are shown in Table 8.

| Weights | Embedding | Max length | F$_1$-micro | Training time |
|---------|-----------|------------|-------------|---------------|
| No weights | trainable | 50 | 0.8907 | 1:45:51 |
| LogReg cross-validated weights | frozen | 50 | 0.2023 | 0:17:00 |
| LogReg cross-validated weights | trainable | 50 | 0.8866 | 0:56:00 |
| LogReg cross-validated weights | trainable | 70 | **0.8931** | 1:16:47 |
| Inverse weights | trainable | 50 | 0.8907 | 0:55:59 |

Table 8: Experiments with dbmdz-xxl-cased BERT
Appendix C  Run-time Efficiency

In this Appendix section, we present a simple evaluation on the profiled run-time efficiency of the proposed models. The Logistic Regression model is trained locally on CPU (with 8 concurrent workers), with an Apple M1 @ 3.2 GHz and 16GB memory. On the other hand, the neural models (CNN and BERT) were trained on Google Colab Nvidia K80 @ 0.82GHz and 12GB memory. The training for LR required 73 seconds, extremely less than to 2-epochs BERT (6351s) and 20-epochs CNN (6480s).

The inference times were elapsed from models loaded in Google Colab, with a Intel(R) Xeon(R) CPU @ 2.20GHz and 13GB of memory. Inference on the test set (11087 samples) took 0.45s for LR, 1.37s for CNN and 11.87s for BERT.

Appendix D  Shared Task Submission Results in Detail

In this Appendix section, we report the detail test evaluation results for Logistic Regression (Table 9), improved Logistic Regression (Table 10) and BERT (Table 11) submissions.

| Dialect | Precision | Recall | F₁-micro | Support |
|---------|-----------|--------|----------|---------|
| EML     | 0.9721    | 0.7176 | 0.8257   | 825     |
| FUR     | 0.942     | 0.969  | 0.9553   | 1323    |
| LIJ     | 0.9226    | 0.8203 | 0.8685   | 2282    |
| LLD     | 0.9362    | 0.26   | 0.407    | 2200    |
| LMO     | 0.5365    | 0.9608 | 0.6885   | 689     |
| NAP     | 0.8758    | 0.7034 | 0.7802   | 2026    |
| TAR     | 0.6047    | 0.1725 | 0.2684   | 603     |
| VEC     | 0.377     | 0.8244 | 0.5174   | 1139    |
| weighted average | 0.8254 | 0.6718 | 0.6880 | 11087 |

Table 9: LR test results for single languages and dialects.

| Dialect | Precision | Recall | F₁-micro | Support |
|---------|-----------|--------|----------|---------|
| EML     | 0.9455    | 0.7782 | 0.8537   | 825     |
| FUR     | 0.8945    | 0.9743 | 0.9327   | 1323    |
| LIJ     | 0.8569    | 0.8554 | 0.8561   | 2282    |
| LLD     | 0.9312    | 0.3568 | 0.5159   | 2200    |
| LMO     | 0.4687    | 0.9681 | 0.6316   | 689     |
| NAP     | 0.8364    | 0.7621 | 0.7975   | 2026    |
| TAR     | 0.4833    | 0.1924 | 0.2752   | 603     |
| VEC     | 0.4313    | 0.6260 | 0.5107   | 1139    |
| weighted average | 0.7908 | 0.6952 | 0.7058 | 11087 |

Table 10: Improved LR test results for single languages and dialects.

| Dialect | Precision | Recall | F₁-micro | Support |
|---------|-----------|--------|----------|---------|
| EML     | 0.9489    | 0.7661 | 0.8478   | 825     |
| FUR     | 0.9542    | 0.9448 | 0.9495   | 1323    |
| LIJ     | 0.9081    | 0.7533 | 0.8235   | 2282    |
| LLD     | 0.9727    | 0.0486 | 0.0926   | 2200    |
| LMO     | 0.5833    | 0.9753 | 0.7300   | 689     |
| NAP     | 0.8830    | 0.4654 | 0.6096   | 2026    |
| TAR     | 0.7455    | 0.0680 | 0.1246   | 603     |
| VEC     | 0.3176    | 0.8964 | 0.4690   | 1139    |
| weighted average | 0.8352 | 0.5759 | 0.576 | 11087 |

Table 11: Improved LR test results for single languages and dialects (late submission, not ranked).
Appendix E  Confusion Matrices for CNN and BERT Models.

In this Appendix section, we include the confusion matrices for CNN and BERT predictions on the development set (Figure 7).

Figure 7: CNN (left) and BERT (right) confusion matrices.