Location-based Twitter Filtering for the Creation of Low-Resource Language Datasets in Indonesian Local Languages

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Abstract

Twitter contains an abundance of linguistic data from the real world. We examine Twitter for user-generated content in low-resource languages such as local Indonesian. For NLP to work in Indonesian, it must consider local dialects, geographic context, and regional culture influence Indonesian languages. This paper identifies the problems we faced when constructing a Local Indonesian NLP dataset. Furthermore, we are developing a framework for creating, collecting, and classifying Local Indonesian datasets for NLP. Using twitter’s geolocation tool for automatic annotating.

1 Introduction

Indonesia is the world’s fourth most populous country, on December 30, 2021, Indonesia’s population is estimated to be 273 million people spread across 17,508 islands (Dukcapil Kemendagri, 2022). Indonesia is home to around 700 languages, accounting for 10% of the world’s total and ranking second only to Papua New Guinea in terms of language diversity (Kohler, 2019). However, most of these languages are not well mentioned in the literature, many are not taught professionally, and there is no universally accepted standard among speakers of these languages (Novitasari et al., 2020). Due to the growing popularity of "Bahasa Indonesia" as an official language, as the primary written and spoken language throughout the country, a number of these local languages are experiencing a decline in usage. Finally, this pattern may result in the emergence of a nation with a single language (Aji et al., 2022).

Many of Indonesia’s indigenous languages are endangered, numbering more than 400. According to data from Ethnologue (Lewis, 2022), which is depicted in figure 1, there are 440 languages that are categorized as endangered, and 12 that are categorized as extinct. Anindyatri and Mufidah (2020) discovered that nearly half of a sample of 98 local Indonesian languages were endangered, and 71 out of 151 local Indonesian languages had fewer than 100k speakers, according to their research.

![Image showing language diversity and speaker count](image)

Figure 1: According to Ethnologue, Indonesia has around 700 languages spoken. Up: Language liveliness. Down: Amount of speakers (Lewis, 2022)

For the NLP technique to be relevant in the Indonesian environment, it must also consider the dialects of the indigenous languages spoken there. In Indonesia, language dialects are influenced by their speaker’s geographical location and regional culture (Vander Klok, 2015). As a result, they can differ significantly in morphology and vocabulary, challenging natural language processing systems. In this study, we will highlight the challenges we encountered when developing a dataset for a natural language processing system utilizing the native Indonesian language. And a framework for creating, collecting, and classifying Indonesian Local Language into datasets for the NLP system. And investigating the geolocation tool on Twitter for automatic annotation.

Our framework comprises of three phases. The
Table 1: Displays the number of speakers of Indonesian and the ten most widely spoken local languages in Indonesia according to Ethnologue (Lewis, 2022)

| Language         | ISO | # Speakers |
|------------------|-----|------------|
| Indonesian       | ind | 198 M      |
| Javanese         | jav | 84 M       |
| Sundanese        | sun | 34 M       |
| Madurese         | mad | 7 M        |
| Minangkabau      | min | 6 M        |
| Buginese         | bug | 6 M        |
| Betawi           | bew | 5 M        |
| Aceh             | ace | 4 M        |
| Banjar           | bjn | 4 M        |
| Balinese         | ban | 3 M        |
| Palembang (musi) | mus | 3 M        |

The first phase is filtering widely used foreign language tweets from Indonesian local Twitter using fasttext (Joulin et al., 2016) to automatically detect language. The second phase is to split the tweet into the formality or informality of an Indonesian text. We choose BERT (Devlin et al., 2018a) as our pre-training model since it has been thoroughly researched by Indonesian scholars. The last phase is we try to classify tweets into the area where the tweet was made. According to our findings, getting local language data from the Twitter dataset can be beneficial, but it also presents its own unique set of challenges.

2 Problem Formulation

The majority of Indonesians speak Indonesian in formal forum, with respected individuals, such as teachers and government officials, as well as with those who do not belong to the group. Because virtually everyone in Indonesia is fluent in the language, and because the Indonesian people consider utilizing Indonesian as a means of communication to be respectable. While the local language is only spoken among the local community, it has numerous variants in written form due to the lack of standardization efforts, making gathering local language data in written form is challenging. As a result, we will design a framework for automatically generating, collecting, and classifying data in 33 Indonesian cities using Twitter geolocation. This is because manually collecting datasets is costly and time-consuming.

3 Related Works

3.1 Multilingual Local Indonesian NLP

There have been several pretrained multilingual language models proposed recently, including BERT dataset in twitter format (Koto et al., 2021), mBART (Liu et al., 2020), and mT5(Xue et al., 2020). On the other hand, their coverage is limited to languages that require a lot of resources. In addition to Minangkabau, Sundanese, and Javanese, only mBERT and mT5 include Indonesian native languages, namely Javanese, Sundanese, and Minangkabau, although with just a tiny amount of pretraining data.

The majority of multilingual datasets do not include the Indonesian language, and just a tiny number of them include Indonesian regional languages. One exception is the WikiAnn dataset (Pan et al., 2017), a weakly supervised named entity recognition dataset covering several Indonesian local languages, including Acehnese, Javanese, Minangkabau, and Sundanese. WikiAnn is a weakly supervised named entity recognition dataset created by Pan et al., 2017. CommonCrawl; Wikipedia parallel corpora such as MediaWiki Translations and WikiMatix; the Leipzig corpora, which include Indonesian and top five spoken local Indonesian and include Acehnese, Buginese, Banjar, and Balinese; and JW-300. On the other hand, recent research has raised concerns about the quality of multilingual corpora for minority languages, mainly linguistic diversity. Although a dataset for local languages has been compiled, it does not contain as much information as the ethnologue (Lewis, 2022) claim that there are 700 spoken languages.

3.2 Local Indonesian Languages NLP System

Relatively little effort has been done on indigenous languages. Several studies investigated stemming Sundanese (Suryani et al., 2018); Balinese (Subali and Fatichah, 2019) and POS Tagging Sundanese (Suryani et al., 2018); Balinese (Subali and Fatichah, 2019) and Madurese (Dewi et al., 2020). A comparable corpus of Indonesian Minangkabau words, as well as sentiment analysis tools for Minangkabau, were created by Koto (Koto and Koto, 2020). Another group of researchers worked on developing machine translation systems between Indonesian and local languages, such as Dayak Kanayatn (Hasbiansyah et al., 2016), Sambas Malay (Ningtyas et al., 2018), and Buginese (Apriani et al., 2016). Some researcher investi-
gated the segmentation of Javanese characters in non-Latin scripts.

3.3 Local Indonesian Collection Challenge

3.3.1 Resources are limited

Insufficient language resources is the most urgent issue with low-resource languages. While there are over 712 languages spoken in Indonesia, the availability of information for each is extremely unequal. For example, Typically, linguistic resources in Indonesian local languages are restricted to formal Indonesian and the top 10 regional languages as in table 1 (Lewis, 2022). In Indonesia, practically all news organizations and news websites use formal Indonesian, as do communications, legal documents, and books; only a small number of books mention specific local languages. Therefore, the compilation of the dataset itself is an issue and challenging.

3.3.2 Differences Between Dialects

Depending on the geographic region, Indonesian native languages can have multiple dialects. Even though they are designated as the same language, the local languages of Indonesian spoken in different regions may differ (have lexical differences) from one another (Fauzi and Puspitorini, 2018). For instance, Anderbeck (2012) in table 2 shown that Jambi Malay dialects vary between villages in the province of Jambi. Similar to Javanese in the Lamongan exhibits up to 13 percent lexical diversity between districts shows in table 3. Similar investigations on other languages, such as Balinese (Maharani and Candra, 2018) and Sasak have been undertaken (Sarwadi et al., 2019).

We show further instances of lexical diversity in indigenous Indonesian languages. Maharani and Candra (2018) and Sarwadi et al. (2019) demonstrate lexical differences in Balinese and Sasak, respectively, by requesting translations of frequent words from native speakers. Then, they compared the language of various locales (villages in this case) to one another. The examples are presented in tables 4 and 5. Pamolango (2012) did a similar experiment at 31 observation stations for the Saluan language in the Banggai district of South Sulawesi. While Pamolango (2012) did not provide complete instances, they observed a lexical variety of up to 23.5 percent among 200 words from the basic vocabulary.

3.3.3 Code-switching

A code switcher or sometime called code-mixer is a person who uses two or more languages in conversation. Throughout a dialogue, a code-switcher shifts between two or more languages (Doğruöz et al., 2021). This occurs frequently in Indonesian speech. People may merge their native languages with standard Indonesian in their speech, producing informal Indonesian. This casual version of Indonesian is spoken daily and is common on social networking websites. Even non-native speakers of the local languages can understand several regularly used code-mixed words, notably on social media. Code-switching can also develop in border zones when individuals are exposed to multiple languages, merging them together. Examples of code-switching is in table 6 (Aji et al., 2022).

3.3.4 Unbalanced Local Indonesian monolingual data.

Unlabeled corpora are essential for the construction of large language models, such as BERT (Devlin et al., 2018b) or GPT-2 by Open AI (Radford et al., 2019). Indonesian-language unlabeled corpora such as Indo4B and Indo4B-Plus (Wilie et al., 2020) mostly contain data in Indonesian, with the latter including a small amount of data in Javanese and Sundanese as well. For example, multilingual corpora such as CC–100 (Conneau et al., 2019) contain only small amount (0.001% of the total corpus size) of Javanese, while mC4 (Xue et al., 2021) contains only 0.6 million Javanese and 0.3 million Sundanese tokens out of a total of 6.3 million tokens. In addition, we compare the availability of data in Wikipedia to the number of speakers to determine data availability. When compared to European languages with equal numbers of speakers, there is significantly less information accessible for the languages spoken in Indonesia. According to Wikipedia, for example, Italian pages take up more than 3 GB of space whereas Javanese articles take up less than 50 MB, despite the fact that both languages have a similar number of native speakers. For the same reason, the articles in Sundanese are less than 25 megabytes in size, whereas languages with comparable numbers of speakers have more than 1.5 gigabytes in size. Similar tendencies can be observed in the majority of other Asian languages. In contrast to European languages with few speakers, the vast majority of other Indonesian native languages do not have Wikipedia pages. The majority of alternative sources for high-quality text
Table 2: The Jambi Malay language has lexical variety among the province’s several communities (Anderbeck, 2012)

| English | Krama Ngoko |
|---------|-------------|
| Eastern | Central Western |
| Why     | ogo’o ngopo ngapa |
| Will    | kate ate arep arep |
| I/me    | aku aku inyong enyong |
| You     | kwen, kowe, kowe, ko |
| How     | yo’opo piye priye |
| Not/no  | gak ora ora |

Table 3: Javanese dialects and styles vary lexically in different locations of the island of Java. It is requested that native speakers translate the terms

| English | Jimbaran | Unggasan | Kedonganan |
|---------|----------|----------|------------|
| Swallow (vb) | Gélék, ngélék | Ngélék, ngélék | Gélék, ngélék |
| How     | Engken   | Kengen   | Engken     |
| Afternoon | Sanjé  | Sanjano  | Sanjé      |
| Where   | Dijé     | Di joho  | Dijé       |
| Scratch (vb) | Gagas  | Guuk    | Gagas      |
| I/me    | Tyang    | Aku      | Tyang      |
| Hat     | Topong   | Cecapil  | Tetopong   |
| You     | Béné     | Engko    | Béné       |
| Dawn    | Ptimunan | Sémongan | Ptimunan   |
| Cough (vb) | Dékah  | Kohkohan | Kokohan    |
| Umbrella | Pajéng  | Pajong   | Pajéng     |
| All     | Onyé     | Konyangan, onyang | Konyangan |

Table 4: Variation in the vocabulary of the Balinese language found in various communities located in the South Kuta district of Bali (Maharani and Candra, 2018)

| English | Jimbaran | Unggasan | Kedonganan |
|---------|----------|----------|------------|
| Swallow (vb) | Gélék, ngélék | Ngélék, ngélék | Gélék, ngélék |
| How     | Engken   | Kengen   | Engken     |
| Afternoon | Sanjé  | Sanjano  | Sanjé      |
| Where   | Dijé     | Di joho  | Dijé       |
| Scratch (vb) | Gagas  | Guuk    | Gagas      |
| I/me    | Tyang    | Aku      | Tyang      |
| Hat     | Topong   | Cecapil  | Tetopong   |
| You     | Béné     | Engko    | Béné       |
| Dawn    | Ptimunan | Sémongan | Ptimunan   |
| Cough (vb) | Dékah  | Kohkohan | Kokohan    |
| Umbrella | Pajéng  | Pajong   | Pajéng     |
| All     | Onyé     | Konyangan, onyang | Konyangan |

3.5 Labeling Datasets with Twitter’s Geotagging Service

The data from Twitter is linguistically varied and contains tweets written in a large number of languages and dialects with limited resources. Having a Twitter geo tagging service that can help us collect large amounts of unlabeled text in low-resource languages. This text can then be used to enrich models for a variety of downstream natural language processing tasks (Banaei et al., 2020). This motivated the author to utilize Twitter databases to automatically crawling and label local Indonesian language data.

3.6 NLP Transfer Learning

In the field of Natural Language Processing (NLP), neural network topologies such as recurrent neural networks (RNNs) (Rumelhart et al., 1985) and convolutional neural networks (CNNs) (LeCun et al., 1995) have demonstrated significant improvements in performance. However, deep learning models...
in NLP perform poorly compared to deep learning models in Computer Vision. This poor development may be due to the lack of large tagged text datasets. Most labeled text datasets are too small to train deep neural networks, which have many parameters and overfitting occurs when trained on tiny datasets.

Deep learning in computer vision relies on transfer learning. Large labeled datasets, such as ImageNet, were used to train deep CNN-based models. Google’s transformer model in 2017 repopularized natural language processing (Vaswani et al., 2017). Transfer learning in NLP allows for high efficiency in a wide range of tasks. A deep learning model trained on a huge dataset can be used on another (Ruder et al., 2019). This is a pre-trained deep learning model. Transformer-based models for NLP tasks arose quickly. Using transformer-based models has many benefits, the most important: Instead of processing input sequences token by token, these models can be expedited using GPUs. These models don’t need labeled data. We simply need unlabeled text to train a transformer-based model. This model can classify, identify, and generate text. We will use BERT (Devlin et al., 2018b) to categorize text using a pre-trained BERT model.

BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2018b) is a large neural network design with 100 million to 300 million parameters. Overfitting occurs when a BERT model is trained on a tiny dataset. So, as a starting point, employ a pre-trained BERT model on a large dataset. The model can then be fine-tuned using our smaller dataset. Techniques for fine-tuning Train the complete architecture. We can feed the output of the pre-trained model to a softmax layer. In this situation, the model’s pre-trained weights are modified based on the new dataset. Frozen layer training – Partially training a pre-trained model is also possible. We can freeze the weights of the model’s first layers while retraining only the upper levels. We can test how many layers to freeze and how many to train. Freeze the model’s layers and add our own neural network layers to train a new model. During model training, just the associated layers’ weights will be updated.

### 4 Proposed Framework

As discussed in Chapter 3.3, the challenges to establishing a dataset for regional languages are: (1) Resources are limited (2) Differences Between Dialects (3) code-switching (4) too many variations of writing and no writing standards. Therefore, we suggest that a framework is required to address the aforementioned issues. This work has multiple sides that can be completed; nevertheless, We will focus on developing a framework for efforts to automatically generate, collect, and classify datasets in tweets from 33 different provincial capitals retrieved over three years (2017 to 2020).

As seen in Figure 2, we will divide the task into three parts, the first of which is the creation phase: developing a monolingual local language from Twitter by collecting as many tweets as possible that are automatically labeled with geographic
locations (33 cities crawled for three years). The second phase is the Filtration Phase (Unsupervised). During this phase, Twitter is filtered between foreign and local languages, and then the local language is filtered between formal and colloquial languages. The third phase, Classification Phase (Supervised), identifies the location from which a tweet is sent.

Figure 2: the work will have three parts. First, create as many geotagged tweets as possible. Second, Filtration (Unsupervised) classified by foreign, local, and formal/colloquial languages. Third part Classification Phase (Supervised) detects tweet origin.

4.1 Phase 1: Creating Monolingual dataset for model pretraining efforts

Language evolves with its speakers. Larger-spoken languages will have a bigger digital presence, which will encourage more written forms of communication, whereas smaller-spoken languages will stress the spoken form. Some regional languages are also declining, with speakers preferring to adopt Indonesian over their own mother tongue. On the other hand, there are residents who live in isolation and speak the local language but they lack proficiency in the use of technology. Twitter users are extremely uncommon in this society.

Twitter is a medium that can be accessed and is quite popular in Indonesia, and it can also be used as an unsupervised automatic dataset annotation. The majority of tweet data in Indonesian regions use Indonesian, English, mixed languages, and informal language, while local language is used the least.

The issue is that only a few tweets have geolocation data revealing where the tweet was sent. Previous research (Sloan et al., 2013) indicates that around 0.85% of tweets are geotagged, indicating that the longitude and latitude coordinates of the tweeter at the time the tweet was written are logged. Within three years of crawling Twitter, we obtained surprisingly little material. Figure 3 illustrates the geotagging map that we created.

4.2 Phase 2: Collection

In this second phase, we employ Fasttext to distinguish between foreign and local languages (including Indonesian). Not all foreign languages are utilized often in Indonesia, for instance. Although Mandarin is one of the most widely spoken languages in the world, it is infrequently used in Indonesia. Therefore, we only filter English, Japanese, Korean, and Arabic, which are the most popular foreign languages.

We employ filters to supervise the classification of formal Indonesian against non-formal languages (which can include colloquial, mixed, and regional languages) since it is easier to filter formal Indonesian. Therefore, we construct a training set consisting of formal and informal languages.

Most language detectors utilize a method to identify the language being used; this becomes problematic if the language is a low-resource language, even if it is blended with another language. For instance, between 20 and 30 percent of modern Javanese speakers combine Javanese with Indonesian or other languages. Javanese is the second most commonly spoken language in Indonesia. The majority of Indonesians speak both Indonesian and their native tongue. Problematically, while communicating in writing, especially via social media, Indonesians tend to utilize colloquial Indonesian rather than their native tongue.

Instead of using language detection, we will use negative detection, that is, collect informal tweets, namely tweets that are not formal Indonesian, and not foreign languages.

4.3 Phase 3: Classifying

Many Indonesian regional languages are spoken and lack an orthographic system. Some indigenous languages have their own historic writing systems inherited from the Jawi or Kawi alphabet; standard transliterations into the Roman alphabet for some (e.g., Javanese and Sundanese) are not generally known and practiced (Soeparno, 2015). Because the sound is the same, several words have multiple romanized orthography that is mutually recognizable. Indonesian regional languages have diverse written forms.
For NLP systems that use word-based representation, this variation increases vocabulary sizes and presents the issue of matching spelled representations of the same term. This phase is the most difficult one.

After collecting local, mixed, and informal language data, we will attempt to fine-tune the BERT model generated during pretraining. Here, we annotate supervised training data with the location where the tweet was made. Despite the fact that these tweets were collected in 33 locations over the course of three years, the resulting data is insufficient and unbalanced.

5 Experiment Setup

5.1 Experiment 1

We chose BERT as our pre-training dataset because it has been extensively investigated by Indonesian scholars. The first experiment will determine whether an Indonesian text is formal or colloquial. Using three pretrained BERT models, namely indolem-indobert-uncased (Koto et al., 2020), indonesia-bert-base-522M (Wilie et al., 2020), and indobertweet-base-uncased (Koto et al., 2021).

1922 of 3844 manually annotated tweets have formal language, while the remaining 1922 contain colloquial expressions. The data is then separated into 0.70 training data, 0.15 testing data, and 0.15 validation data.

By executing it for 50 fine-tuning epochs. With dropout layer = 0.1, activation function = ReLU, Layer 1 = Linear (768,521), Layer 2 = Linear (512,2), and the final layer’s activation function is softmax, the text is classified as formal or informal Indonesian. The acquired findings are then presented in table 8.

From table 8, it can be concluded that the indobertweet-base-uncased dataset is optimal for classifying formal and informal language in our dataset. This makes sense, as the dataset employs a mixed Indonesian Twitter dataset as the pretraining dataset.

| Data Statistics          | Value         |
|--------------------------|---------------|
| Crawl time period        | 2017-2020     |
| Cities (Table 8)         | 33 Cities     |
| Tweet total              | 1,326,099     |
| foreign language         | 271,861 (20.5%)|
| formal Indonesian        | 111,843 (9.9%)|
| informal Indonesian      | 922,755 (69.6%)|

Table 7: Data statistics, including the date and location of data crawling, as well as total data tabulation.
### Table 8: Formal Indonesian and colloquial Indonesian were classified by comparing the outcomes of three previously trained BERT models

| Existing Pretrained Bert Datasets | Precision | Recall | F1-Score | Accuracy |
|----------------------------------|-----------|--------|----------|----------|
| indolem                          | 0.8       | 0.85   | 0.86     | 0.78     | 0.81     | 0.82     |
| indobert                         | 0.84      | 0.86   | 0.87     | 0.84     | 0.85     | 0.85     |
| indonesia-bert-base-522M         | 0.86      | 0.9    | 0.91     | 0.86     | 0.89     | 0.88     |
| indobertweet-base-uncased        | 0.86      | 0.9    | 0.91     | 0.86     | 0.89     | 0.88     |

5.2 Experiment 2

After achieving the optimal pretrained and fine-tuned model in the first experiment, the second experiment will consist of acquiring a Twitter dataset incorporating local languages. This is achieved by eliminating tweets containing frequently-used foreign languages on Indonesian local Twitter.

As indicated in figure 3 and table, geotagged tweets are collected from 33 distinct regions in Indonesia. Facebook’s FastText is used to reduce the number of tweets written in other languages that are commonly spoken in Indonesia, such as English, Japanese, Korean, and Arabic. Then, the data is depicted in graph in figure 5.

5.3 Experiment 3

In the first experiment, it was determined that the use of pretrained BERT indobertweet-base-uncased was the most applicable for Twitter dataset, and a model was developed to differentiate between formal and informal languages in experiment 2 in the section 5.2. In this experiment, the model from the first experiment was utilized to differentiate the use of formal and informal language in distinct Indonesian regions. This experiment produced an intriguing pattern, as depicted in Figure 6. Formal Indonesian is a language that is mastered by all regions in Indonesia. However, in this low-resource experiment, formal language is regarded as noise because it does not represent a particular region where local languages and dialects are used. Therefore, formal language is separated from informal language used in the region.

5.4 Experiment 4

Given the mixed data of informal and local languages on Twitter discovered in Experiment 3, the final model is constructed to categorize the col-
lection of tweets by the region from which they originated. This is used to determine which local languages are spoken in the area. This is possible due to Twitter’s geolocation tagging feature, which may be used to annotate the tweet’s location.

Using machine learning, we identify very few original statements in a given location; instead, there is code mixing or terms from many languages. It is not possible to extract terms that exclusively use local languages based on this research because Twitter users are often intended for the broader public, hence the majority use national and mixed languages (colloquial languages). To be able to entirely isolate the local language, more advanced approaches or even hand annotation are required; however, this is not an option due to its high cost.

6 Analysis of Experimental Outcomes

There are interesting findings from the separation of formal and informal (including regional languages), with manual searches found that there are only less than 1% of tweets that use regional languages. This finding is quite surprising, because the authors expect more tweets in regional languages in certain regions. Even in areas with small tweet volumes, such as Manukwari, most tweets are dominated by Indonesian, both formal and informal. So that more aggressive filtering is needed to remove colloquial language with more sophisticated techniques.

Case study, the city of Surabaya, where the author currently lives, and the author’s native language is Javanese, we conducted a manual search, using Twitter in Javanese in the city of Surabaya, which should be dominated by Javanese and using Javanese in daily conversation, but we found that less than 1 percent of tweets used the local language, and the rest were a mixture of languages. It indicates that Anindyatri and Mufidah (2020) claim that the use of regional languages is beginning to decline is very credible.

7 Future Works

Expensive GPU requirements limit our research. Instead of establishing another huge model, we advise developing lightweight and fast neural architectures, such as by distillation (Jiao et al., 2019), model factorization, or model pruning (Voita et al., 2019). Non-neural approaches remain popular among Indonesian academics. Further research on the trade-off between model efficiency and quality is also interesting.

8 Conclusion

The framework that we built has the ability to reduce and filter out non-local languages by up to 30.4%. This has never been done by researchers in Indonesia; yet, 30% is still lacking because 70% of these tweets are a mixture of colloquial language and code switching to dominate tweets. Less than one percent of the tweet is local language (we manually search with random samples). There are many things that can be explored in the case of collecting datasets for local languages in Indonesia. We need even more aggressive filtering, because to distinguish whether an informal sentence is colloquial, code-mixing or pure regional language, more data is needed, we need to enter manual data by native speakers, this cannot be done by the author due to lack of resources.

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| City          | Latitude   | Longitude  | Raw Tweet | Foreign | Indonesian | Indonesian Colloquial+Local |
|--------------|------------|------------|-----------|---------|------------|-----------------------------|
| Ambon        | -3.62553   | 128.190643 | 13998     | 2930    | 11068      | 1859                        | 9209                        |
| Banda Aceh   | 3.5912     | 98.69175   | 62618     | 9477    | 53144      | 9208                        | 43933                       |
| Bandar Lampung | -5.39714 | 105.266792 | 44377     | 5046    | 39331      | 4752                        | 34579                       |
| Bandung      | -6.917464  | 107.619125 | 60724     | 11459   | 49265      | 5522                        | 43743                       |
| Banjarmasin  | -3.318607  | 114.594376 | 42195     | 7501    | 34949      | 5699                        | 29995                       |
| Bengkulu     | -3.577847  | 102.34639  | 26947     | 2523    | 24424      | 3377                        | 21047                       |
| Demapasar    | -8.670358  | 115.212631 | 61463     | 23770   | 37693      | 3737                        | 33956                       |
| Gorontalo    | 0.699937   | 122.446724 | 22750     | 2751    | 19999      | 2453                        | 17546                       |
| Jakarta      | -6.17511   | 106.85036  | 129594    | 29647   | 99947      | 7319                        | 92628                       |
| Jambi        | -1.610123  | 103.631121 | 30747     | 3668    | 27079      | 3634                        | 23445                       |
| Jayapura     | -2.591603  | 140.66906  | 11961     | 2482    | 9479       | 1505                        | 7974                        |
| Kendari      | -3.99846   | 122.512978 | 30190     | 3031    | 27169      | 3443                        | 23716                       |
| Kupang       | -10.1772   | 123.607033 | 15422     | 3671    | 11751      | 1539                        | 10212                       |
| Maros        | -2.69919   | 118.852106 | 8041      | 746     | 7295       | 886                         | 6409                        |
| Manado       | 1.47483    | 124.82079  | 47531     | 13845   | 33686      | 3386                        | 30300                       |
| Manokwari    | -0.861453  | 134.062042 | 2677      | 345     | 2332       | 422                         | 1910                        |
| Mataram      | -8.597081  | 116.108487 | 55077     | 14887   | 40190      | 4980                        | 35210                       |
| Medan        | 3.595196   | 98.672226  | 56768     | 12941   | 43857      | 5169                        | 38688                       |
| Padang       | -0.947083  | 100.417183 | 44670     | 8881    | 37589      | 5171                        | 36018                       |
| Palangka Raya| -2.216105  | 113.913979 | 15109     | 2338    | 12771      | 1791                        | 10980                       |
| Palembang    | -2.976074  | 104.775429 | 49133     | 9682    | 39451      | 4580                        | 34871                       |
| Pala         | -0.86791   | 119.904655 | 28067     | 2926    | 25141      | 3571                        | 21570                       |
| Pangkalpinang| -2.22487   | 106.124649 | 22534     | 2437    | 20097      | 3358                        | 16739                       |
| Pekanbaru    | 0.507068   | 101.44777  | 48397     | 6845    | 41552      | 6148                        | 35404                       |
| Pontianak    | -0.02633   | 109.342596 | 37239     | 8732    | 29307      | 4020                        | 24457                       |
| Samarinda    | -0.494823  | 117.143616 | 37991     | 6717    | 31274      | 3915                        | 27359                       |
| Semarang     | -7.085145  | 110.438126 | 58337     | 9424    | 48913      | 6282                        | 42631                       |
| Serang       | -6.110366  | 106.163979 | 61871     | 14117   | 47754      | 5359                        | 42395                       |
| Sofifi       | 0.734965   | 127.561447 | 7432      | 1740    | 5692       | 978                         | 4714                        |
| Surabaya     | -7.257472  | 112.75209  | 59690     | 12828   | 46862      | 5230                        | 41632                       |
| Tanjung Selo | -2.69844   | 115.057664 | 43409     | 19247   | 24162      | 2945                        | 21217                       |
| Tanjungpinang| 1.040912   | 104.440659 | 29399     | 5140    | 24259      | 2507                        | 21752                       |
| Yogyakarta   | -7.79558   | 110.369492 | 59741     | 10117   | 49624      | 6738                        | 42886                       |

Table 9: The tabulation of all experimental (2,3,4) results in a single data table