Gender Prediction Based on Vietnamese Names with Machine Learning Techniques

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Abstract—As biological gender is one of the aspects of presenting individual human, much work has been done on gender classification based on people names. The proposals for English and Chinese languages are tremendous; still, there have been few works done for Vietnamese so far. We propose a new dataset for gender prediction based on Vietnamese names. This dataset comprises over 26,000 full names annotated with genders. This dataset is available on our website for research purposes. In addition, this paper describes six machine learning algorithms (Support Vector Machine, Multinomial Naive Bayes, Bernoulli Naive Bayes, Decision Tree, Random Forrest and Logistic Regression) and a deep learning model (LSTM) with fastText word embedding for gender prediction on Vietnamese names. We create a dataset and investigate the impact of each name component on detecting gender. As a result, the best F1-score that we have achieved is up to 96% on LSTM model and we generate a web API based on our trained model.

Index Terms—Gender detection

I. INTRODUCTION

Gender prediction based on human’s names is a topic on which a vast number of researches are investigating [1]–[2]. There have been large numbers of investments on identifying the most suitable algorithms and models for different languages. The reason behind for these researches is the potential benefits of predicting two common genders (Male and Female). Consequently, there are a variety of online web applications and tools that are capable of pointing out the gender from user’s first name [3]–[6].

These existing gender predicting systems are useful and practical in terms of third-party APIs providers for other applications [7]. A typical utilization is online registration forms and documents. For instance, giving a form where the users have to fill up their names and genders, the application will automatically choose the corresponding gender field after the users have typed in their names. Predicting gender eliminates the amount of time which the users need to away from keyboard and click on computer mouse or track-pad to check on the field. It enhances the overall user experience while using the services.

In addition, the co-reference resolution is a Natural Language Processing task to which gender classification is possible to be applied. The co-reference mission is to identify the same entity that all the objects in one text are referring. For example, “James is having dinner with Mia. He is having beef steak.”. In this scenario, He is referring to James which is a Male. Therefore, determining gender of a given name is sufficiently essential to mark references to correct entity [8].

On the other hand, not many related researches on Vietnamese names have been done over the years. Thus, the goal of this paper is to perform gender classification on Vietnamese names using machine learning models. From there, we can study further on the naming conventions and how efficient the machine learning algorithm predicts the genders using Vietnamese names.

In this paper, we have three main contributions described as follows:

- First, we build a new dataset for analysing Vietnamese names called UIT-ViNames. The dataset consists of 26,852 Vietnamese full names annotated with 1 for male and 0 for female. UIT-ViNames is available for research purposes at our website.
- Second, we experiment new implementations and comparison of multiple traditional machine learning and deep learning models on predicting genders on our dataset. As a result, LSTM model with fastText word embedding achieves the highest average score with 95.89%.
- Lastly, we perform analyses on Vietnamese names which provides a deeper understanding on naming convention and increases the efficiency of using traditional machine learning and deep learning for gender prediction.

In Section II, we perform literature review on previous studies. Then in Section III, we describe the our dataset and how we collect it. Next, we present a detailed description on our approach for this topic in Section IV and our experiments in Section V. Finally, in Section VI we draw an overall conclusion and several future works.

II. RELATED WORK

In previous related works, there are several approaches for English languages, while there are few proposals for Vietnamese. Koppel et al. [1] provided a methodology on identifying genders of written document’s authors. They combined syntactic and lexical features on the subset of BNC dataset. The experimental result was about 80% which was the outcome of POS n-grams.

Peersman et al. [2] described an approach for classifying genders on social networks. The authors collected the data from Netlog which is a Dutch social network. They performed SVM technique for this short text classification task. The

1https://sites.google.com/uit.edu.vn/uit-nlp/
highest accuracy score was 88.8% when applying 50,000 most
information word unigrams.
In terms of tools, GenderAPI [6] and NameAPI [8] are
the most common used among the community. However, their
drawback is obvious which includes limited dictionary and
not open-sourced. In addition, the prediction accuracy on
languages such as Chinese and Russian is fairly low. Zhao and
Kamareddine [16] proposed an advance application based on
existing tools within the UK, Malaysia and China. The average
performance of their prediction system was 96.5%.
In more recent study, Jia and Zhao [4] described a novel
approach utilizing fastText word embedding on BERT-based
model to classify genders based on Chinese names. In their
paper, they provided a comparison on traditional models,
namely Naive Bayes, GBDT and Random Forest. As the result,
they achieved 93.45% test accuracy on BERT-based model.

Panchenko and Teterin [5] proposed an approach on Russian
names for gender classification task using linear supervised
model. The experiment was performed on a dataset of 100,000
full names from Facebook using n-grams, word embedding
and dictionary features. The authors reported that the model
performance reached up to 96% of accuracy.

As the languages differentiate among nations and regions,
a study on the component of names are necessary to further
understand how their impacts on genders. Since Chinese is
a logo-syllabic language [17], the approaches for this task
are focusing on the character itself. In contrast, Vietnamese
language is based on Latin alphabet which is similar to
English. Therefore we only consider and compare the charac-
teristic Vietnamese names to English names. Le [11] defined
that Vietnamese name has three components, respectively Họ
(surname/family name), Tên Đệm (middle name) and Tên
(personal name). According to Le’s research, the official order
of Vietnamese name is differ from English names. Specifically,
in English, the order of name component is first name, middle
name, and family name (surname). For example, John Doe
consists of John (personal name) and Doe (family name).
In a comparison, family name is placed as last component
in English name, while in Vietnamese name, it is place at
first position. In next section, we describe the data collection
procedure and analyze the dataset in details.

III. DATASET
In this section, we present how we collect the data and
analyze it distributions and characteristics. Our method of
dividing Vietnamese name into components is derived from
Le’s study [11] since it provides a baseline for investigating
Vietnamese names. We evaluate each individual component
in order to determine its weight of efficiency in identifying
genders.

A. Dataset Collection
Our data is collected from several universities in Vietnam.
The students in those universities come from provinces and
cities across Vietnam, so that it diversifies the collection of
data and covers a wider range of names. Additionally, the data
only contains names and genders which avoids revealing the
identities of the students. The name field includes full names
of the students which are annotated with two labels (Male
and Female). Our dataset consists of 26,852 samples of which
proportion of two labels is fairly balance. The percentage of
male and female, respectively, is 57.71% and 42.29%.

Table I
EXAMPLES FOR MALE AND FEMALE NAMES.

| No. | Full name                        | Gender |
|-----|---------------------------------|--------|
| 1   | Võ Minh Đủ (Vo Minh Du)        | 1      |
| 2   | Nguyễn Thị Hiền (Nguyen Thi Hien)| 0      |

B. Dataset Analysis
In the context of recognizing individual genders, there are
evidences showing that people’s last names have a lower
impact than first names (including middle name) [12]. We also
close the distributions of last names in male’s comparing
to female’s for our dataset which are shown in Figure 1.

Figure 1 illustrates that the most common Vietnamese last
names for both males and females are identical. This is a
concrete evidence for the fact that, in Vietnamese names, last
name has zero or very low impact on determining genders.
This fact is also proven through our experimental results in
Table IV. Hence, we only consider first names and middle
names in the gender predictions. The distribution of first
names of Vietnamese males and females is compared in
Figure 3. In comparison, those figures demonstrating the
common Vietnamese first names have the words density that
are significantly higher than of which the Vietnamese last
names. It is clearly shown that Nguyễn (Nguyen) is the most
usual Vietnamese last names. There are researches showing
that approximately 40% of Vietnamese’s last name is Nguyen
which reflects in our dataset as well. Based on Figure 4, it also
indicates the fact that the variety of last names in Vietnamese
is fairly small. This is clearly demonstrated by the densities of
both figures for last names. Figure 2 shows that majority of
Vietnamese male’s middle names are Minh (Minh) and Văn
(Van); which on the other side, Thị (Thi) is widely applied
for naming females.

Figure 1. The distribution male and female last names in Vietnamese.
IV. OUR APPROACHES

In this section, we present a description on the research methods implemented in this paper as well as the reason why we come up with the decisions on choosing models. We define this problem as a binary classification task since there are two labels (Male and Female) needed for this task. The purpose of this paper is to figure out the most efficient machine learning technique for detecting gender based on names, therefore, we implement commonly used models which namely are Naive Bayes Bernoulli, Naive Bayes Multinomial, Support Vector Machine, Logistic Regression, Decision Tree, Random Forest and deep learning model - Long short-term memory.

A. Pre-processing Data

The data collected has been gone through two steps of pre-processing. Firstly, we cut off all the last names and those are stored separately in two dictionaries which are male’s last name and female’s last name. We have discovered that last names have inconsiderable influence on genders which is also clearly stated in Section III. Next, we perform cleaning data by removing special characters, double spacing, and correct the misspellings. We also convert the names into lower case in order to strengthen the integrity for our data. Data deduplication is an important step that excludes all the duplicates in our dataset. Consequently, we obtain a set of full names with no extra spacing and special characters.

B. Gender-prediction Models

1) Naive Bayes: Naive Bayes is a widely applied for text classifier [13], and especially, gender predictions using English and Chinese names [3]. The basic formula of Naive Bayes classification algorithm is:

\[ P(c \mid w) = \frac{P(c) \times P(w \mid c)}{P(w)} \]

This formula calculates the probability of a given \(w\) (word) belongs to a class \(c\). Specifically, \(P(c \mid x)\) is the posterior probability of class \(c\) given predictor \(x\). \(P(c)\) is the prior probability of class. \(P(x \mid c)\) is the likelihood which is the probability of predictor given class \(c\); \(P(x)\) is the predictor’s prior probability [14]. This is the base theorem that is applied for Multinomial and multivariate Bernoulli models.

Multinomial (Multinomial NB) is specially design for text classification by identifying the appearance frequency of a specific word in documents [15]. Consider, in our case, there are some specific words in Vietnamese names having higher likelihood of presence in one gender. For instance, Thị (Thi) is used for naming females while Văn (Van) is commonly in a male’s name. Thus, Multinomial model is a decent choice for this classification task.

Multivariate Bernoulli Naive Bayes Classifier (BNB) model is moderately similar to the Multinomial algorithm in terms of classification process. In comparison, BNB model focuses on the present state of a word on the documents under consideration while Multinomial model approach, as mentioned, considers the term frequency in documents [16].

Furthermore, Table II shows the most common first names of Vietnamese males and females. In particularly, it points out that Anh is the one that appears frequently in both Male and Female names. For example, Tuấn Anh (Tuan Anh) is more likely a Male while Tú Anh (Tu Anh) has higher percentage to be a Female. This observation suggests that a simple first name is not enough to robustly classify the genders. Therefore, middle names are necessary in order to rank up the possibility of detecting genders correctly.

| Rank | Male Names | Female Names |
|------|------------|--------------|
| 1    | Huy (Huy)  | Linh (Linh)  |
| 2    | Tuấn (Tuan)| Thao (Thao)  |
| 3    | Đạt (Dat)  | Nhi (Nhi)    |
| 4    | Duy (Duy)  | Trang (Trang)|
| 5    | Hậu (Hieu)| Anh (Anh)   |
| 6    | Anh (Anh) | Nguyễn (Ngan)|
| 7    | Minh (Minh)| Ngọc (Ngoc)|
| 8    | Nam (Nam)  | Như (Nhu)    |
| 9    | Long (Long)| Thù (Thù)   |
| 10   | Bảo (Bao)  | Vy (Vy)      |
2) Support Vector Machine (SVM): We utilize SVM because it provides a superior method for text classification using kernel function to handle nonlinear spaces [17]. Theoretically, SVM is implemented to find the best possible way to separate the given dataset where the distance between the nearest point to the support vector is longest [15]. In our case, this algorithm is utilized and measured because our goal is to figure out the most efficient method to obtain the best predictions. In order to achieve this objective, firstly, each word of the names is converted into multi-dimensional vectors. The Vietnamese names have some words that both frequently appear in two labels, thus, SVM algorithm in this scenario is able to provide a better results on predictions.

3) Logistic Regression (LR): Logistic Regression is another discriminative algorithm that we would like to investigate its capability of determining genders using Vietnamese names. Logistic regression could be applied for text classification task since its usage is to express the relationship between the dependent binary variables and independent variables [18]. Specifically, the binary variables in our classification problem are male and female, and the independent variables are the words in names.

4) Decision Tree (DT): Decision Tree is a classification technique that represents each feasible outcome into each possible result using branching method [19]. DT is composed of three basic types of node which are root, internal leaf, leaf. DT uses a set IF-ELSE rules to do decision making. Farooqui et al. [20] clearly stated that DT’s performance is much higher when the classification involved decision making. In our task, each individual word in a name has a weighted influence towards one gender. This techniques is capable of defining the relationship between the dependent and independent variables so that it is a decent choice to experiment.

5) Random Forest (RF): Random Forest is an ensemble algorithm that comprises multiple decision trees. We use this uncorrelated model to compare with DT model. Theoretically, as RF uses a large number of uncorrelated trees to predict, it can outperform the individual prediction. Maruf et al. [21] described a new method on Random Forest and Feature Selection (FS) for text classification and achieved macro-F1 score 73% higher than normal FS algorithm.

6) Long Short-Term Memory (LSTM): Long short-term memory is a deep learning model whose architecture includes gates and memory cells. These components allow LSTM to store and retrieve the information through operations such as write, read and reset. Johnson and Zhang [22] investigated one-hot LSTM with region embedding which yields the effectiveness of the approach in categorizing text. We implement this method with fastText word embedding to measure the performance of a deep learning algorithm comparing to traditional machine learning techniques.

V. Experiments

In this Section, we describe the process of setting up the experiments using NB Bernoulli, Naive Bayes Multinomial, Support Vector Machine, Logistic Regression, and Long Short-term Memory as well as examining the outputs of each technique by investigating the confusion matrices and wrong predictions. There are three main steps which are data preparation, experiment configurations and result analysis.

A. Data Preparation

First of all, we randomly divide our dataset into three different subsets: training, development, and test. In our dataset, the proportion of male and female is relatively balance. Thus, each of the subset is designed to maintain this equity and avoid bias against any side. We separate the corpus in the proportion of 70%, 10%, and 20%, for training set, development set, and test set respectively. We start by individually separating the data into training, development and test subset for each gender label. Then, we merge two subsets by their gender label, for example, train set for male is combined with train set for female. After the data has been splitted up, the names (features) are needed to be converted into individual vector. In our experiments, we evaluate Count Vector and TF-IDF features for vectorizing and tokenizing the data.

B. Experimental Settings

Since not many related researches for this task have been published, we based on other previous experiments on text classification to set up our parameters for each model. When tokenizing the names, we also ignore configuring the threshold for maximum and minimum frequently of words. The reason is that the stop words are out of concern so it is not necessary to limit out the repetition. For Count Vector, we use the baseline configuration but for TF-IDF, we set maximum features = 4,000.

After each run, we capture the precision and recall to calculate F1-score as the final results; as well as the confusion matrix to further investigate wrong predictions. Since the results of binary classification task can be divided into four

| Models                | Count Vector |          |          | TF-IDF |          |          |
|-----------------------|--------------|----------|----------|--------|----------|----------|
|                       | Male | Female | Average | Male | Female | Average |
| Multinomial NB        | 95.92 | 94.41  | 95.16   | 95.16 | 93.3   | 94.23   |
| Bernoulli NB          | 96.03 | 94.46  | 95.25   | 96.06 | 94.49  | 95.28   |
| Logistic Regression   | 95.96 | 94.32  | 95.14   | 95.75 | 94.03  | 94.89   |
| Support Vector Machine| 96.06 | 94.49  | 95.28   | 95.75 | 94.20  | 94.89   |
| Decision Tree         | 95.07 | 93.04  | 94.05   | 94.32 | 92.26  | 93.78   |
| Random Forest         | 95.17 | 93.38  | 94.28   | 95.05 | 94.03  | 94.84   |
Table IV

| Name Components | SVM & Count Vector | Bernoulli NB & TF-IDF | LSTM |
|-----------------|--------------------|------------------------|------|
| Family Name     | Male 79.89, Female 5.31, Average 39.60 | Male 73.95, Female 4.49, Average 39.22 | Male 73.29, Female 3.16, Average 38.23 |
| Middle Name     | Male 93.04, Female 89.66, Average 91.35 | Male 89.35, Female 84.48, Average 86.92 | Male 86.26, Female 73.79, Average 80.02 |
| First Name      | Male 89.37, Female 84.71, Average 87.04 | Male 89.36, Female 85.00, Average 87.19 | Male 88.43, Female 81.36, Average 84.90 |
| Family Name + Middle Name | Male 92.86, Female 89.20, Average 91.03 | Male 92.44, Female 88.19, Average 90.32 | Male 91.72, Female 87.89, Average 89.80 |
| Family Name + First Name | Male 89.52, Female 85.50, Average 87.51 | Male 89.36, Female 85.00, Average 87.19 | Male 88.43, Female 81.36, Average 84.90 |
| Middle Name + First Name | Male 96.06, Female 94.49, Average 95.28 | Male 96.06, Female 94.49, Average 95.28 | Male 96.56, Female 95.22, Average 95.89 |
| Family Name + Middle Name + First Name | Male 95.47, Female 93.77, Average 94.62 | Male 95.68, Female 94.08, Average 94.88 | Male 95.67, Female 94.43, Average 95.05 |

classes: True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN), we apply macro average scoring method to calculate F1-score.

On the other hand, in this paper, we apply fastText word embedding for LSTM model as it supports various languages. Grave et al. [23] used fastText for word representation in 157 languages. We set embedding size as 300 and configure batch size = 32 and epoch = 2 in our experiment.

C. Result Analysis

We report the final results of four machine learning algorithms for both tokenizing methods in Table III. The results visually specify that Support Vector Machine produces the best results with count vector method while using TF-IDF. Whereas, Bernoulli Naive Bayes reaches the highest performance among other traditional machine learning methods. However, Table V yields that deep learning model - LSTM reaches the best F1-score of 95.89%. Specifically, we record the best precision, recall and F1-score of all traditional machine learning models in comparison with LSTM. As a result, the deep learning model - LSTM achieve the best experimental performance on our dataset.

Table VI

| Middle and First Name | True Gender | Prediction |
|-----------------------|-------------|------------|
| Đức Phượng (Duc Phuong) | 1           | 0          |
| Đặng Tú (Dang Tú)    |             |            |
| Trần Lâm Anh (Tran Lam Anh) |       |            |
| Trần Thục Vy (Tran Thuc Vy) |        |            |
| Trần Uyên Quang (Tran Uyen Quang) | 0     | 1          |
| Gia Hao (Gia Hao)     |             |            |
| Minh Tuyên (Minh Tuyen) |   |            |
| Từ Văn (Tu Van)     |             |            |
| Minh Ngọc (Minh Ngoc) |             |            |
| Y Duy (Y Duy)        |             |            |

We notice that the results in both cases are approximately equivalent. By inspecting the wrong predictions, we discover that the similarity in wrong classification results. The term frequency of name component is the factor of this confusion. For instance, Figure [2] displays that the words Ngôc (Ngoc) or Thanh (Thanh) frequently appear in Vietnamese female’s and male’s middle names. Table VI is a list of examples of misclassification for two labels which we to further analyze the factors causing errors. In both cases, we notice that there are some words appear in male names which are normally chosen when naming females and vice versa. For example, Phượng (Phuong), Tú (Tu), Lâm Anh (Lam Anh), Thục Vy (Thuc Vy), and Uyên (Uyen) are regularly in female names, however in our dataset, they are in male names. In contrast, Hảo (Hao), Tuyền (Tuyen), Văn (Van), Minh (Minh), and Duy (Duy) are typically male’s names but not female’s.

Figure 4. Confusion Matrix of Count Vector with SVM and TF-IDF with Bernoulli NB (Normalized)

Additionally, the F1-score for females are always lower
than males in all cases. The confusion matrix in Figure [4] demonstrates the error distribution in determining male in comparison with female names. It shows that in two scenarios, the correct predictions for male always higher than females. Specifically, the wrong prediction percentages of which female names are classified as males are 7.5% and 7.4%.

We also conduct ablation experiments in which we systematically remove name components of the input to understand their impact on Vietnamese gender prediction. In this examination, we only utilize SVM with Count Vector, Bernoulli Naïve Bayes with TF-IDF and LSTM since they give the best outputs in this task. Table [V] is the results when we run the test on seven (7) name combinations. They indicate the fact that the concatenation of middle name and first name outperforms the others. The results again strengthen the proclamation that Vietnamese surnames have remarkably low impact on detecting genders. This experiment also yields the importance of Vietnamese middle names in gender detection task. Its achievements among other standalone name components is highest with the average of 91.35% using SVM with Count Vector, 90.94% using Bernoulli Naïve Bayes with TF-IDF and 92.07% on LSTM.

VI. CONCLUSION AND FUTURE WORK

In this paper, we have presented several approaches for gender classification task based on Vietnamese names. Our experiment is conducted on six (6) traditional machine learning techniques and one (1) deep learning model. LSTM deep learning model reaches excellent result on our UIT-ViNames dataset which is up to 96%. Hence, we also generate a simple web API service based on this LSTM pre-trained model. In our experiment, we also show the importance of Vietnamese middle name when detecting gender. In conclusion, the analyses on our dataset and experimental results show that Vietnamese family names have low influence on genders, while middle names are the most important as well as LSTM model produces the best F1-score on gender detection task. In future work, we try to solve the issues of wrong prediction on majority of female names. We also plan to expand the name diversity in our dataset and study the efficiency of transfer learning models such as BERT and other deep learning models on this task.

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| Traditional Machine Learning | Precision  | Recall   | F1-score  |
|------------------------------|------------|----------|-----------|
| Multinomial NB               | 95.28      | 95.06    | 95.16     |
| Logistic Regression          | 95.30      | 94.87    | 95.14     |
| Support Vector Machine       | 95.57      | 95.05    | 95.28     |
| Decision Tree                | 94.44      | 94.77    | 94.60     |
| Random Forest                | 94.98      | 94.73    | 94.87     |
| Deep Learning                | LSTM       | 96.11    | 95.70     | 95.89     |
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