MACHINE LEARNING MODEL TO PREDICT THE DIVORCE OF A MARRIED COUPLE

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ABSTRACT

Divorce usually impacts the closest family members, over the years the divorce rate has increased dramatically, especially in the last two decades and worsening with the pandemic, where there has been a significant increase in the divorce rate in many countries of the world. We draw on Yöntem's work where he poses 56 questions as predictors of divorce. In addition, we make use of 4 automatic learning models (perceptron, logistic regression, neural networks and randomized forest) and 3 hybrid models based on voting criteria. Each of these models was trained in 5 different scenarios, making a total of 35 experiments, the best performance obtained in terms of precision, sensitivity and specificity is 0.9853, 1.0 and 0.9667 respectively, corresponding to the perceptron model and a hybrid model; however, although the results show a high performance, the context, the amount of data and the country in which the data were collected must be considered.

KEYWORDS

Machine learning, Neural networks, Divorce predict, Voting.

1. INTRODUCTION

The divorce rate worldwide has increased dramatically in recent years. This assertion is based in figures. First, is the American divorce rate. If we compare the figures for 2018 with those of 1900, it shows that there are four times more divorced women (Schweizer, 2020). In Spain, this rate doubled (2018) compared to 2000 (INE, 2018). In Mexico, such rate tripled from 2000 to 2019 (INEGI, 2019) and in Peru the number of divorces registered in 2018 (INEI, 2018) is eight times higher than those registered in 2000 (INEI, 2010).

The current pandemic context has only exacerbated this phenomenon, as the confinement has brought with its greater increase. This applies for the United States, which, in couples with at least 5 years of marriage, registered 16% more divorces in the third quarter of 2020 than in the same period of 2019 and an increase of 5% in couples with children that have less than 18 years (Legal Templates, 2020). An even more noticeable case occurs in Xi'an (China) where divorce requests have increased to such an extent that they have reached their daily limit (Díez, 2020). Naturally, this situation has consequences that can affect close members of the families involved (Sánchez, 2019).

In this regard, different studies have identified multiple factors to predict divorce. One of the most significant works was that of Gottman. He identified "The Four Horsemen of the Apocalypse" that can end a marriage: criticism, contempt, stonewalling and defensiveness (Gottman & Silver, 2014). Using just these four variables in a longitudinal study conducted with newlywed couples, Gottman estimated which couples would have an early divorce with 85% accuracy. Gottman also identified that quality sexual satisfaction, love, and passion in marriages depend directly (by 70%) on the quality of friendship they have (Gottman & Silver, 2015). On the other hand, there are studies that show infidelity as the main ground for divorce. This is not surprising: infidelity is the leading cause of divorce in the United States (Mark, Janssen, & Milhausen, 2011) as well as in more than 160 cultures (Betzig, 1989), because it has negative effects on the relationship, and can be the most feared and devastating experience in a matrimony (Pittman, 1994), thus leading it to an end (Zordan & Strey, 2011).

In the last decade, the use of Machine Learning models in psychology has become popular, leaving behind numerous methods of estimation, statistical analysis and data mining for

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predictions. In the first place is Amiriparian, who used audio spectrograms to diagnose bipolar disorder (Amiriparian *et al.*, 2019), obtaining an Unweighted Average Recall (UAR) of 46.2%. Second are Eastwick and Joel, who used a random forest method to predict the appereance of a relationship based on traits and preferences; out of 192 couples, it was able to predict 4% to 18% of actor variance (average tendency to romantically desire other people) and 7% to 27% of the partner variance (to be desired by other people) (Joel, Eastwick, & Finkel, 2017). Finally, Flesia's work predicted the stress levels that are caused by COVID-19 from 18 psychosocial variables, achieving a sensitivity of 76%.

For the particular case of the prediction of divorce, we checked the following background: the work of Großmann *et al.* (2019), which used a linear regression model to predict the future of a relationship based on the analysis of personality traits, the work of Yöntem *et al.* (2019) with ANN models that achieved a precision of 98.85% and the work of Narendran, Abilash & Charulatha (2020) that made use of a voting classifier with decision trees, bagging classifier and XGBoost prediction models, achieving a performance of 94.14%.

Using fresher classification methods, the present work aims to compare the high performance obtained with an analysis based on the correlation of variables, making available the proposed models and their respective trained results.

2. MATERIALS AND METHODS

2.1. DATASET

In this research we will use the same dataset as the one in Yöntem's *et al.* work (2019) which is composed of 54 questions. 6 of them can be seen in Table 1: they were answered by 170 people –84 divorced and 86 married–. As divorce predictor, each question had different probabilities of impact. Answers are on a 5-point scale (0 = Never, 1 = Rarely, 2 = Average, 3 = Often, 4 = Always).

Table 1. Questions formulated in Yöntem's work.

ID	Questions
Atr1	If one of us apologizes when our discussion deteriorates, the discussion ends.
Atr2	I know we can ignore our differences, even if things get hard sometimes.

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Atr3	When we need it, we can take our discussions with my spouse from the beginning and correct it.
…	…
Atr52	I wouldn't hesitate to tell my spouse about her/his inadequacy.
Atr53	When I discuss, I remind my spouse of her/his inadequacy.
Atr54	I'm not afraid to tell my spouse about her/his incompetence.

Source: adapted from (Yöntem *et al.*, 2019).

2.2. PREPROCESSING

Data normalization is one of the preprocessing approaches where the data is scaled or transformed to obtain an equal contribution from each characteristic, thus translating into a significant improvement in the performance of Machine Learning algorithms (Singh & Singh, 2019). In this work, the 54 questions contain numerical data between 0 to 4, values that were re-scaled between -1 and 1, as shown in Figure 1.

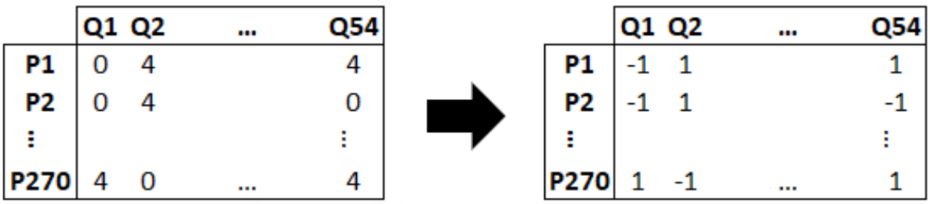

Figure 1. Normalization of the answers.
Source: own elaboration.

2.3. FEATURE SELECTION

Considering each question as a characteristic, we use Pearson's correlations for the selection. Thus, we measure the degree of relationship between the variables (Liu *et al.*, 2020). Table 2 shows the 20 variables with the highest correlation.

Table 2. Question with the highest correlation.

Id	Score	Id	Score
Atr22	0.7853	Atr42	0.6423
Atr54	0.7685	Atr48	0.6336
Atr28	0.7621	Atr53	0.6114
Atr44	0.7530	Atr47	0.5827
Atr34	0.7498	Atr52	0.5755
Atr32	0.7397	Atr45	0.5102
Atr50	0.7254	Atr43	0.4822
Atr31	0.6992	Atr7	0.4280

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Atr51	0.6841	Atr46	0.4003
Atr49	0.6748	Atr6	0.2871

Source: own elaboration.

2.4. CLASSIFICATION

For the classification, this work uses four models of Machine Learning. The first is the Perceptron model, with a stop criterion of 1e-4. The second model is a logistic regression with lbfgs as the optimization parameter. The third model are neural networks, composed of 7 layers, as seen in Figure 2, all with a sigmoidal activation function and 30 epochs for their training. The fourth is a Random Forest model with 100 estimators and a depth of 2. Generally, hybrid models based on voting criteria have superior performance (Kuncheva & Rodríguez, 2012; Liu, Reviriego, Lombardi, & Hernandez, 2020), for which 3 hybrid models were created from the 4 models mentioned. The classification models can be seen in Table 4.

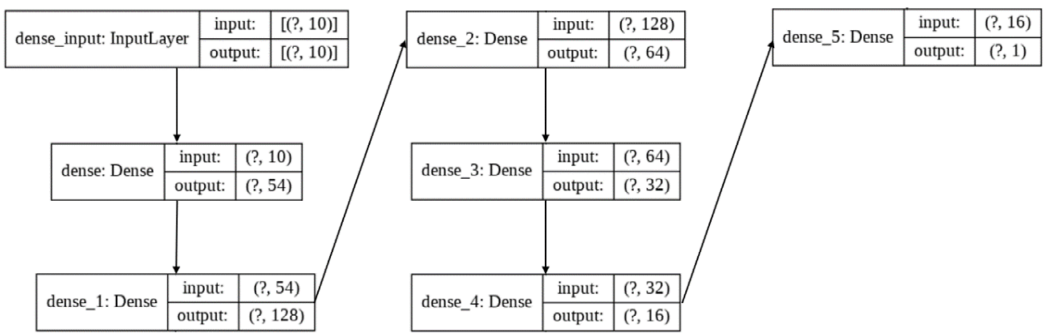

Figure 2. Architecture of a neural network model.
Source: own elaboration.

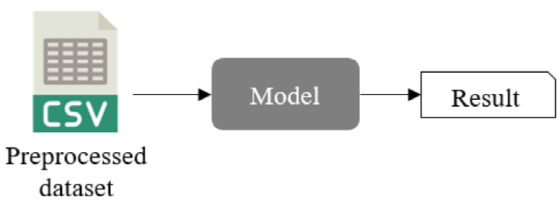

Figure 3. Training scheme for each model.
Source: own elaboration.

For the training, test and training data was randomly divided, in the proportions shown in Table 3. Each model was trained with the scheme in Figure 3.

Table 3. Proportion of training and test data.

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Label	Proportion (%)					
		50/50	60/40	70/30	80/20	90/10
Divorced	Training	42	50	59	67	76
	Test	42	34	25	17	8
Married	Training	43	52	60	69	77
	Test	43	34	26	17	9

Source: own elaboration.

Table 4. Models used for prediction.

ID	Models
M1	Logistic Regression
M2	Neural Networks
M3	Random Forest
M4	Perceptron, Logistic Regression and Neural Networks
H1	Perceptron, Neural Networks and Random Forest
H2	Perceptron, Logistic Regression and Random Forest
H3	Perceptron

Source: own elaboration.

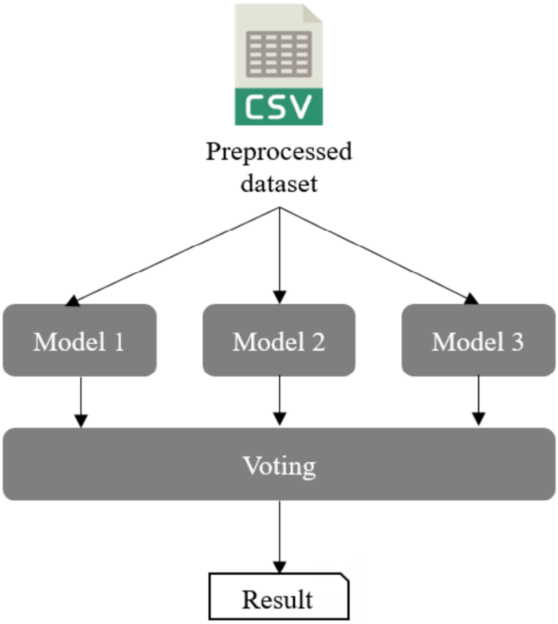

Figure 4. Voting criteria for hybrid models.
Source: own elaboration.

The proposed model was implemented using Python 3 in Google Colab (Carneiro, Medeiros, & Nepomuceno, 2018) using a 2.3 GHz Xeon CPU with 13gb RAM and a 16gb RAM Nvidia Tesla V100 graphics card.

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2.5. EVALUATION

To measure the performance of the classification, the proposed model used performance metrics in terms of sensitivity (Sen), specificity (Spe) and Accuracy (Acc).

A divorced person properly classified is called "true positive" (TP). A divorced person that is not properly classified is called "true negative" (TN). When a divorced person is classified as married, it is called a "false negative" (FN), and when a married person is classified as divorced, it is called a "false positive" (FP).

Sensitivity shows divorced people correctly classified, defined as (Lyusin & Ovsyannikova, 2016):

$$Sensitivity = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{1}$$

Specificity shows divorced and married people properly classified. It is calculated as follows (Glaros & Kline, 1988):

$$Specificity = \frac{\mathrm{TN}}{\mathrm{TN+FP}} \tag{2}$$

Accuracy indicates the ratio of correctly classified people, obtained with the formula (Pedersen, Cheng, & Rasmussen, 1989):

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+FP+TN+FN}} \tag{3}$$

On the other hand, hybrid models are evaluated by the voting criterion (see Figure 4), where the label that was repeated the most is selected.

3. RESULTS

In this work, multiple experiments were generated with the four models defined in the "classification" section. These were trained with the proportions defined in Table 3. When training the model with the Yöntem work dataset, the results of Table 5 are obtained.

Table 5. Accuracy results of the training.

	Training/Test (%)				
Model	**50/50**	**60/40**	**70/30**	**80/20**	**90/10**
Perceptron	0.9529	0.9853	0.9608	0.9412	0.9412
Logistic Regression	0.9412	0.9559	0.9804	0.9706	0.9412

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Neural Networks	0.9647	0.9559	0.9804	0.9706	0.9412
Random Forest	0.9294	0.9412	0.9804	0.9706	0.9412
H1*	0.9647	0.9853	0.9804	0.9706	0.9412
H2*	0.9412	0.9706	0.9804	0.9706	0.9412
H3*	0.9412	0.9706	0.9804	0.9706	0.9412

Source: own elaboration.

Table 6. Sensitivity results of the training.

	Training/Test (%)				
Model	**50/50**	**60/40**	**70/30**	**80/20**	**90/10**
Perceptron	0.9783	1.0000	0.9630	0.9444	1.0000
Logistic Regression	1.0000	1.0000	1.0000	1.0000	1.0000
Neural Networks	1.0000	1.0000	1.0000	1.0000	1.0000
Random Forest	1.0000	1.0000	1.0000	1.0000	1.0000
H1*	1.0000	1.0000	1.0000	1.0000	1.0000
H2*	1.0000	1.0000	1.0000	1.0000	1.0000
H3*	1.0000	1.0000	1.0000	1.0000	1.0000

Source: own elaboration.

Table 7. Sensitivity results of the training.

	Training/Test (%)				
Model	**50/50**	**60/40**	**70/30**	**80/20**	**90/10**
Perceptron	0.9231	0.9667	0.9583	0.9375	0.9000
Logistic Regression	0.8718	0.9000	0.9583	0.9375	0.9000
Neural Networks	0.9231	0.9667	0.9583	0.9375	0.9000
Random Forest	0.8462	0.8667	0.9583	0.9375	0.9000
H1*	0.9231	0.9667	0.9583	0.9375	0.9000
H2*	0.8718	0.9333	0.9583	0.9375	0.9000
H3*	0.8718	0.9333	0.9583	0.9375	0.9000

Source: own elaboration.

4. CONCLUSIONS

In this work, 7 models were used for the prediction of divorce, trained with the dataset from Yöntem's *et al.* (2019) work and the dataset collected in this research. Each of these models was trained in 5 different scenarios, making a total of 35 experiments. Among these, the best results were obtained with the perceptron model and the first hybrid model; however, due to the amount of data, the hybrid models did not perform better.

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Although the results show high performance, the context, the amount of data and the country in which the data was collected must be considered. In order to feed the dataset to retrain the models, in the future we plan to collect couple's data from different countries, evaluating their performance.

Divorce is a major problem, especially in a context of confinement, where the rates of divorced couples have increased considerably, indirectly affecting the closest members of the family (such as children). Also, couples can lose a lot by going through a divorce process. This study can help them prevent these consequences. The prediction models in this study would help people decide whether to make the decision to marry or not, give them the opportunity based on compatibility to have a successful marriage.

The best performance of a model was obtained by using the 60/40 ratio of the training and test data. The results were 0.9853 precision, 1.0 sensitivity and 0.9667 specificity. We make the models and training results available in our GitHub repository (https://github.com/NahumFGz/DivorcePredict).

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