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Comparative Studies of Supporting Vector Machines and Artificial Neural Networks for Scheduling Optimization

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***Abstract*— This project is to construct an improved clinic scheduling and flow system for optimization. Providing a solution to this issue will require determining the main clinic scheduling problem and figuring out what hardware and software issues are needed to be solved. We took an approach to optimize the appointment schedule by training and comparing various Machine Learning models such as Supporting Vector Machines and Artificial Neural Networks, and pick the model with the best performance for the scheduling optimization. The software framework was developed based on the Django web server with the Scikit-Learn Machine Learning library from Python.**

***Keywords*— Machine Learning, Supporting Vector Machines, Artificial Neural Networks**

I. Introduction

Scheduling optimization of appoint booking in clinics and hospitals will result in significant budget saving and efficiency improvement [1-4]. The goal of this project is to use Machine Learning method to maximize the appointment completion rate. Currently, there are many inefficiencies in how time slots are allocated to patients. Patients have to book their appointments in-person and receive infrequent reminders about their appointments causing cancellations and delays. If hospital does not receive payments from the missed appointments, it will result in a loss of revenue. The physicians are spending more time than necessary idling when they should be treating and diagnosing more patients. Many appointments could be cancelled during their lunch break. Finally, patients that need to have their health check-ups are not being seen, which can result in bad health for the patients. In some cases, where a patient's check-up appointment is mandatory, missing their checkup can result in even worse outcomes. By using the Machine Learning method, we have designed a solution that can effectively improve the rate of successful appointments. Also, by combining the Machine Learning program with the Django web framework, a web user interface was made for the ease of using this solution. The two models that we picked performed different characteristics under training environment. Each model has its own advantage and weakness. For the MLP Classification model, it has short training time, better accuracy and recall rate. It is a more balanced model compare to SVC. MLP Classification will be a better model in applications where all types of classification results are considered, and the training time is limited. SVC will be a better model when training time is sufficient, and only one type of classification result is used [5-8]. Our project as the capabilities to be easily implemented in current system. It has little to no interaction with any current software being used. The algorithm could be applied to most clinics or hospitals with some fine-tuning. This means our project could potentially be implemented on a hospital-wide scale. The issues that could arise from this are defining and discovering what factors need to be considered for optimization. In terms of usability, some training may be required in order for current and new employees. The training wouldn't be very complicated and the functionality of our software is very self-explanatory and familiar to typical search or ad hoc functions. There are some alternative ways this project could be implemented into the current system in place at the hospital. Our software could be integrated into the scheduling software already in use at the Hospital, Epic. The software scope could be increased, instead of handling it piecewise clinic to clinic, have it optimized the whole hospital.

II. Project Implementation

A. Picking Model

The Database that we used for our project is Microsoft SQL Server. For the user interface, we are using the web based interface hosted by Django Web Server. For the Machine Learning models, we are using the Scikit-learn library in Python. Using Both the Web Framework and Neural Network Model in Python allows us to integrate both programs together with the ease of importing functions and classes from other programs. For the Machine Learning models, we have selected Neural Networks and SVM classification as our candidate models. We picked the Neural Network as our approach since it has the ability to learn hidden relationships in the data without manually mapping any fixed relationships in the data.

B. Feature Engineering

The raw data need to be converted to features that can be used by the Machine Learning models. The string values such as Procedure Name and Provider Name will be defined as categorical values. Since models cannot multiply strings by the learned weights, we use feature engineering to convert strings to numeric values. For the values that are continuous and integer, we will convert it to float value, such as converting 6 to 6.0. For the date and time value, we convert them to units of year, month, day, hour, minute and weekday. For example, "2018-10-22 20:48" will be converted to [2018, 10, 22, 20, 48, 1]. The last value "1" represents the Monday,

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and it is counted from 0 to 6, represented by Sunday, Monday, to Saturday. We add weekdays to our feature because the weekday could be a factor affecting people's behavior and appointment results. For example, lots of people take off earlier on Friday rather than Tuesday, and lots of people struggle to go to class on Monday rather than Wednesday. For the binary value such as "NoShow Flag" in the raw data, we are going to convert it to 0 and 1 since it only has null and "Y" value.

There are some columns in the raw data that we excluded, such as "Cancellation_Reason". This column describes the cancellation reason after the appointment cancellation. The reason is these data are the results happened after the inputs, and our Neural Network model is only designed to predict the complete or fail status of the appointment. Therefore, the "Cancellation_Reason" is useless to our Neural Network model [7]. In order to find the best fitting features, a logic was created for the Neural Network Training program. This logic cycles the Training through every possible combination and finds the one with the highest accuracy. Also, the effect of input features on the output result are not known, by taking out some of the features, the accuracy of the models can be varying. Or, by creating more input features, the output accuracy can be improved. Example of creating more input features can be adding patient appointment record for each event, the day of the week of each appointment. The reason of adding those features is that those features could affect the prediction record. A patient with bad appointment attendance would have lower chance to attend his next appointment, and depend of the day of the week, the patient can have different attitude.

III. Training

A. Performance Score

In this case of combining different input, we looped every possible combinations and take the model with the highest accuracy. For our project, we used the precision of our model's score on successful appointment prediction as our objective. The reason of the choice is because users are going to pick only successful appointment schedule on the web interface to book appointments, and based on this schedule logic, numbers of actual successful appointment should be maximized to reach this project goal - improve the appointment completion rate. The higher the precision on successful appointment, the higher the score is.

B. Training Data

For the Neural Network model, we checked all meaningful combinations of options in parameters that would maximize the model performance. Our parameters are selected and divided into several fields: Activation Function, Size of Hidden Layer, Learning Rate, etc. As a result, those parameters produced 3024 combinations.

Table 1: The parameters for tuning Neural Network model

Parameters	Options
Activation	Identity, logistic, tanh, relu
Solver	LBFGS, SGD, Adam
Alpha	0.01, 0.003, 0.001, 0.0003, 0.0001, 0.00003
Hidden Layer Sizes	(23, 3), (23, 7), (23, 7, 3), 23, 30, 17
Learning Rate	constant, invscaling, adaptive

We divided the training data into two sets: The Training set and Test set. The training set is a subset to train a model, the Test set is a subset to test the trained model. First, we shuffled the data, then we split 70% of the data to the Training Set, and 30% to the Test. After we have the Training and Test Set, we used the MLP Classification model to train our Neural Network by going through all the 3024 combinations from the parameters. The performance of each combination is recorded to database for further evaluation. This model is trained by using Backpropagation algorithm.

IV. Evaluation

A. Support Vector Classification

For SVM, we picked the SVC (Support Vector Classification) from the Sciki-learn library. With the SVC model, a list of parameters is available for tuning. However, we could not afford the time cost of looping through the combinations of parameters, as each training takes about half-hour which is about 60 time longer than the training time of Neural Network model. We picked a set of fixed parameters for our SVC Model, since tuning is not a feasible option.

Table 2: The parameters for SVC Model

Parameters	Value
C	1
Kernel	Poly
Degree	3
Gamma	auto
Coef0	0.0
Shrinking	True
Probability	True
Tol	0.001
Class weight	balanced
Verbose	True
Decision function shape	ovo

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B. *Evaluation*

The evaluation of the Machine Learning model performance is done by using method of Cross Validation, with K Fold of 5. With higher K Fold value, it comes with more accurate evaluation performance but longer training time. Lower the K Fold value will result in shorter training time, but less accurate evaluation. Having K Fold of 5 is an option that allows fair training time while yield decent evaluation accuracy.

V. Results

Those two models result in different performance. For the MLP Classification model, among the 3024 types of combinations of parameters, the best combination reached 93% of precision on predicting successful appointments. Compare to the MLP model, the SVC model provides higher precision score of 99% on prediction successful appointments too. There are the tables of the classification report of those two models:

Table 3: Best Training Results of two Machine Learning model

Evaluation Type	MLP Classifier	SVC Classifier
Precision	93%	99%
Accuracy	86%	82%
Recall	84%	70%
Training Time	<1 minute	>30 minutes

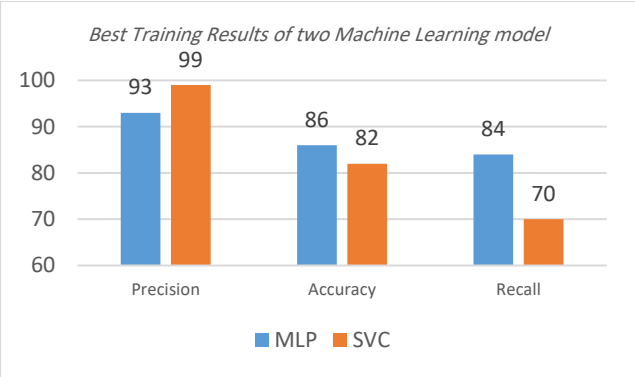

Figure 1. Visualized Data of Best Training Results of two Machine Learning model

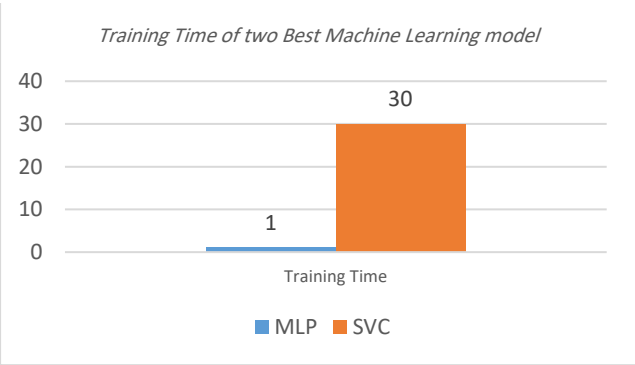

Figure 2: Training Time of two Best Machine Learning model

The following parameters have been chosen for the best Machine Learning performance:

Table 4: Parameters for MLP Classification with best performance

Parameters	Options
Activation	logistic
Solver	adam
alpha	0.0001
Hidden Layer Sizes	(23, 3)
Learning Rate	constant

By evaluating the performance of these two models, SVC Classifier comes on top of those two models with the highest precision score. Therefore, our team pick SVC Classifier as the Machine Learning model for our project application – predicting appointment results.

VI. Conclusions

The proposed solution to the clinic scheduling and flow issue is to produce a recommendation report that has high precision on successful appointments. Hospitals can use this recommendation report as a guide when scheduling appointments in the future. This recommendation report will be produced by feeding information of new appointment to the trained Machine Learning model. Also, by summarizing the overall appointment completion rate, the real-world performance of the Machine Learning model will be visualized on the Django web page.

References

[1] Suyang Zhou, Wennan Zhuang, Zhi Wu, Wei Gu, Siming Cao Multi-parallel work centers scheduling optimization with shared or dedicated resources in low-volume low-variety production systems, Applied Mathematical Modelling, Volume 80, April 2020, Pages 472-505.

[2] Arya Russell, Sharareh Taghipour, Multi-objective optimization of complex scheduling problems in low-volume low-variety production systems, International Journal of Production Economics, Volume 208, February 2019, Pages 1-16.

[3] Ying Mei, Jiawei Ye, Zhigang Zeng, Two-way scheduling optimization of the supply chain in one-of-a-kind production based on dynamic production capacity restrictions, Journal of Manufacturing Systems, Volume 47April 2018, Pages 168-178.

[4] Amir Mohammad Fathollahi-Fard, Mehdi Ranjbar-Bourani, Naoufel Cheikhrouhou, Mostafa Hajiaghaei-Keshteli, Novel modifications of social engineering optimizer to solve a truck scheduling problem in a cross-docking system, Computers & Industrial EngineeringVolume 137, November 2019, Article 106103.

[5] Meenakshi Choudhary, Vivek Tiwari, Venkanna U. An approach for iris contact lens detection and classification using ensemble of customized DenseNet and SVM, Future Generation Computer Systems, Volume 101, December 2019, Pages 1259-1270.

[6] L. A. Demidova, I. A. Klyueva, A. N. Pylkin, Hybrid Approach to Improving the Results of the SVM Classification Using the Random Forest Algorithm, Procedia Computer Science, Volume 1502019, Pages 455-461.

[7] Ons Boujelben, Mohammed Bahoura, Efficient FPGA-based architecture of an automatic wheeze detector using a combination of MFCC and SVM algorithms, Journal of Systems Architecture, Volume 88, August 2018, Pages 54-64.

[8] Karthik Thirumala, Sushmita Pal, Trapti Jain, Amod C. Umarikar, A classification method for multiple power quality disturbances using EWT based adaptive filtering and multiclass SVM, Neurocomputing, Volume 33421 March 2019, Pages 265-274.

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