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Predictive Modelling on Competitor Analysis Performance by using Generalised Linear Models and Machine Learning Approach

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ABSTRACT

Competitive analysis in digital and technology is trending in the business field. However, the field of digital and technology in the business world is vast and challenging to analyse. The purpose of this research is first to identify the success factor which represent the company performance. Second, is to identify the significant services provided by the company to their business user. Then, based on the first and second objectives, a predictive modelling is developed to produce the best solution to their business user. The research is implementing a case study from Telecommunication Company and using data science life cycle methodology. The statistical modelling that is used to develop the competitor's analysis model is generalised linear model (GLM) which integrated with machine learning approach. Furthermore, the synthetic data set is created by using Gamma Distribution, Gaussian Distribution and Poisson Distribution due to some data from the case study is confidential. The synthetic data set is based on existing real data which are from Telecommunication Company sentiment analysis data, were used to investigate the performance of the proposed model. The machine learning technique is used to get the accuracy of the significant GLM which has been developed. The accuracy is tested by using the error rates of the machine learning technique which are Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and R-squared. This research discovered that the business solution to the significant service for the business user and discovered the best statistical model to be used for the business solution. The results show that the Gumbel distribution is the best fit model for the synthetic dataset where the values of RMSE is 1.0574, MAE is 0.9168 and R-squared is 0.3994, and the significant success factor that has been identified by using the GLM is advertising success factor. The model developed can be improved with another type of data set and different sizes of data. Hence, further studies and real-world data are required for better validation.

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1. Introduction

In digital technology services, Each Telecommunication Company has their own specialty that can compete to the other service provider. However, the difference from one to another is the business user that uses their service in their company. Often, a business user is defined as the entity or official organisation which subscribes or use their services, which are government agency, private agency, private company, industry, and individual that use the service from the service provider. The business user that uses cloud service can be from government agency, private company, and industry. Even though certain Telecommunication Company can be one of the largest service providers in Malaysia, it is common and known that there are still other services that more excellent compared to one another in terms of different service elements and the amount of business user which attracted to their service. It is a challenge to the Telecommunication Company to be the number one digital technology service provider in Malaysia.

Competition is the custom in the business world. There are variety of competitions such as digital, marketing, business intelligence, ranking competition etc. To compete in the business competition, basically, the company could analyse the factors which influence the business and the business user to improve their product or services. This research highlights the competitor analysis of certain Telecommunication Company regarding the Cloud service product that has been provided by such Telecommunication Company. Generally, in competitor analysis, statistical modelling and machine learning methods are some of the methods that can be used to analyse the significant factor of the product services specifically by the Telecommunication Company on Cloud services.

As the technology increase, there are many new services provided by the Telecommunication Company. There are multiple telecommunications service in Malaysia and international such as Celcom, Maxis, U Mobile, Digi, Vodafone, TIME, AwanTec, AWS Malaysia, ENFRASYS, MICROSOFT Malaysia, Ali Baba Cloud and Google Cloud Malaysia. All the companies have the same role and purpose which provide network services to the business user. Most of the big companies such as government agency, industry, private company, and individuals use the services that provide by the service provider. However, some of the services are not well known to the people or to newly build company. The services are also expensive to be maintained and accounted to the business user. On the contrary, these services can save a lot of time and energy to get the job or task done faster and managed the workload in efficiently and effectively.

To provide a better business model by such Telecommunication Company, the first objective of this research is to investigate the competitors services by considering the success factor of the companies such as innovation, advertising, brand name, productivity, customer service, price competitive, technological and competence. Second, the business model is developed to predict the business user needs in each of the service provided by the Telecommunication Company.

2. Literature Review

The missions of Telecommunication Company are providing services to customer, through converged lifestyle communication experiences, make ease to business by collaborating with and supporting them with integrated solution, and to make easier to the nation by supporting socioeconomic development through education, innovation, and social initiatives. The industries are Banking, financial services, and insurance (BFSI), government, education, healthcare etc. Bolster competitiveness and create revenue opportunities in BFSI. Most of the Telecommunication Company aim to make great things possible, and to be recognised by leading international technology companies for their excellence and innovation.

Theoretically, studying the actions and behaviour of close competitors is important to strategy the markets. Managers utilise competitive data to gain a better understanding of their industry and competitors, as well as to discover areas where competitors are weak and assess the impact of strategic initiatives on them [9]. Competition is known as one of the trending cultures in today's business world. Even with big or small companies, the competition still involves, and every company requires strategies to compete. Competition is a common feature in any corporates that is involved in any profit-driven organizations. It is possible to find a competitor's weak area as well as opportunities and dangers from the industrial environment by identifying competitors [2]. Competitor analysis is a driving factor behind a company's strategy, influencing how businesses behave and respond in their sectors [3].While competitive analysis is a more specific term than competitor analysis, the two concepts are sometimes used interchangeably in strategic management. Competitive analysis is the process through which a company attempts to define and know its industry, identify, and understand its competitors, assess their strengths and weaknesses, and forecast their moves [7]. Competitive analysis is required to provide a full understanding of the competitive dynamics that occur in the competitive environment of each organisation [1]. The purpose of competitors analysis is to be able to identify a competitor's probable future actions, especially those created in response to the focal business's conduct [2]. This requires both quantitative and information (i.e., what the competition is doing and can do) as well as qualitative and purposeful information (i.e., what the competitor is likely to do).

To overcome the competitor's advantage and own weakness, a company cannot outmanoeuvre its competition without closely observing their behaviour and anticipating their next moves [2]. Tracking other competitor's action can make a firm stay alert on the upcoming events or any updates from the opponent firm [2]. Competitor analysis is therefore critical for small businesses to ensure their business survival. As a result, the current research investigated how small-scale trading businesses deal with competition to boost sales. It was specifically designed to determine the impact of the threat of new potential entrants, substitute products, supplier and buyer bargaining power, and competitor rivalry on the sales performance of trading enterprises [17].

Generally, competitors are businesses that compete for a share of the consumer's spending power. Kotler and Armstrong [6] suggested that there are four types of competitors which are brand competitors, industry competitors, form competitors and generic competitors [6]. In the business world, common consumers usually choose brand as their base choice since bigger brand gives more quality and productivity [2]. Different competitors have their own unique service that can outcome another competitor in terms of quality and productivity [2]. In telecommunication services, the brands alone do not satisfy the customer perspective.

Logically, identifying the competitor factors is important to investigate the competitor's performance. Based on Adom *et al.*, [1], innovation, advertising, brand name, productivity, customer service, price competitiveness, technological and competence are major success factors for the organisation [2]. Competitors Profile Matrix (CPM) is used as a tool for companies to evaluate themselves against their top competitors based on the industry's critical success aspects. Identifying the key success factor is the first step to construct a CPM for a company. Each of the company's significant competitors must be identified, and each of them, including the company itself, must be rated on each of the criteria in the key success factor [2]. Mathematical modelling is an important part of quantitative marketing since it aids organisations all over the world in making critical marketing decisions such as introducing new products and managing existing ones [10], [6]. Most marketing research mathematical models are either pure or semi-pure statistical or contain statistical model parts [21]. Based on the professional statistician viewpoint regarding market modelling field, there are few types of statistical models that are appropriate [12] to use in the market research which will be discussed in the next section. Other than traditional mathematical modelling, machine learning is one of the frequently used recently when dealing with uncertainty and big data [8], [15], [19], [20], [4], [5]. Barboza, F., Kimura, H., & Altman, E. [5] use machine learning models to predict bankruptcy and found that machine learning models show improved bankruptcy prediction accuracy over traditional models [12]. In their study, various models have been assessed by using different accurateness metrics. Resulting that boosting, bagging, and random forest models provide improved results. Recently, Hasan *et al*., [13] has used machine learning to predict employee performance, where they integrate business analytics and machine learning methodology to forecast personnel performance [13]. The model which been proposed has leverages data-driven info from distinct sources, entailing performance metrics, staff data, and contextual factors, to tailor accurate predictive models. The results show the efficiency of the consolidated approach in forecasting workforce performance. Hence, presenting valuable insights for companies to make informed decisions associated with talent management and resource allocation [13]. In addition, machine learning reshapes our comprehension and manipulation of materials by accelerating discovery and enabling tailored design through property prediction models and structure-property relationship [16]. Eisbach, S., Mai, O., & Hertel, G. [11] has used the combination of machine learning and theoretical models which yield both higher predictive accuracy as well as higher explanatory value and lower requirements of data and computational power as compared to either of the two approaches alone [11].

Based on the professional statistician viewpoint regarding market modelling field, there are few types of statistical models that is appropriate to use in the market research which discussed in the next section.

3. Methodology

In this research, the data science methodology is used and implemented. Generally, the data science methodology consists of nine steps which are business understanding, analytic approach, data requirement, data collection, data understanding, data preparation, data modelling, evaluation, and deployment as shown in Figure 1.

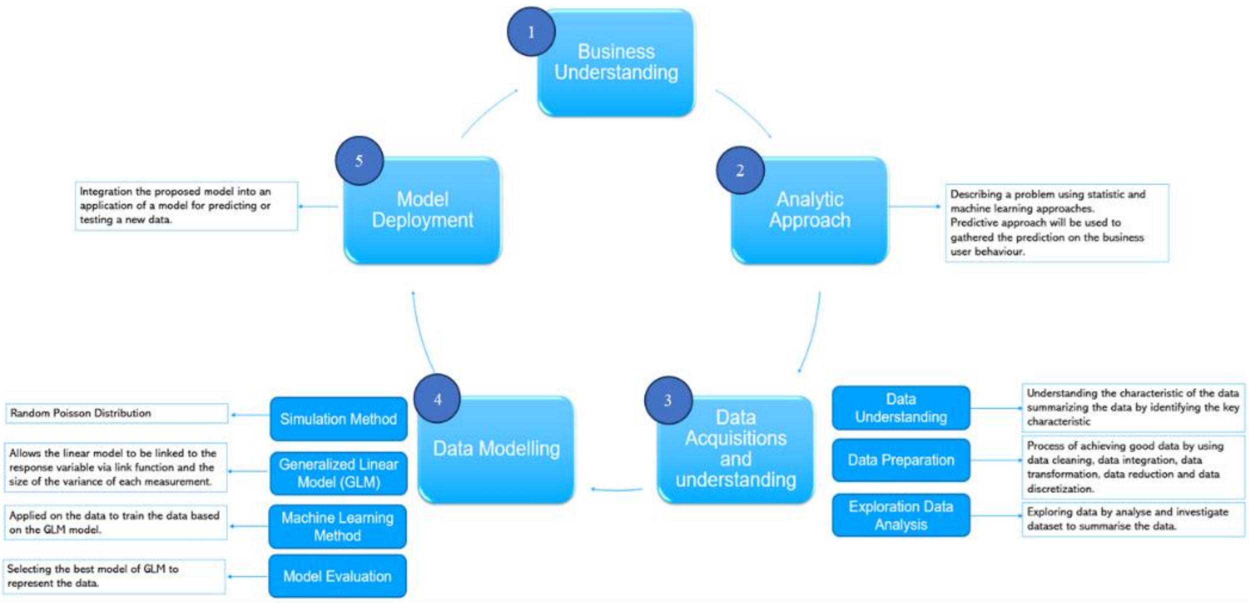

Fig. 1. Data Science Lifecycle

Analytic approach is the process of describing a problem using statistics and machine learning approaches. It is used in the resolution of any data-related problem. In this research, predictive approach is used to perform the research. The information gathered is processed to achieve the prediction on the identifying the key success factor which influenced the Telecommunication Company performance and the choice of the business user in selecting the best service in the Telecommunication Company. The data used are from business user and Telecommunication Company information. The key success factor is used as variable in the model to find the significant service and business solution. A synthetic data set is created based on the proposed model, which been developed based on the key success factor and Telecommunication Company information. The variables considered for the synthetic data are products, connectivity, innovation, and brand name.

Data preparation is one of the important processes in achieving good data to run in model. Data preparation aids in the detection of errors prior to processing. By cleaning and reformatting datasets, data preparation produces high- quality data, ensuring that all da ta utilised in analysis are in an excellent quality. Da ta cleaning, da ta integration, data transformation, data reduction, and data discretization are the five processes in the data preparation. The data and variables which used to create the synthetic data is collected from Telecommunication Company sentiment analysis data (available upon request). The data is collected from the social media mention such as Twitter, Facebook, Instagram etc. The key success factor attainable from the Telecommunication Company sentiment analysis data are products, connectivity, innovation, and brand name. The key success factor is ranked on different ratings from one to four considering their relative importance to the organization where "one" stand for major weakness, "two" stands for minor weakness, "three' stands for minor strength, and "four" stands for major strength, which also measure the performance of the Telecommunication Company.

Then, Exploration data analysis (EDA) is implemented to explore data by analyse and investigate datasets to summarise the data (available upon request). The process also helps to determine how best to manipulate data sources to get the needed output by considering data wrangling, da ta exploration, and data cleaning. In this research, the average performance of Telecommunication Company as the dependent variable and innovation, advertising, brand name, productivity, and connectivity as the independent variables. The modelling that used in this research is generalised linear model (GLM) and the machine learning method that used in this research are k-Nearest Neighbors (KNN), Support Vector Machine (SVM) and Random Forest (RF) models. These methods are used to identify the prediction error rates for each of the methods by comparing which methods has the lowest Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). Furthermore, machine learning method also generate R-squared value by comparing which methods has the highest R-squared value to determine how well the data fit in the regression model. In this research, Akaike information criterion (AIC) is used to evaluate and validate the model of the key success factor data. The model fit test is tested by checking which model has the lowest AIC value.

The simulation method process is done by using R programming language Version 4.1.2 with RStudio software. The data for the simulation is based on the key success factor of the Telecommunication Company. The method of simulation which been used in this research is bootstrap method since the data is considered as classified. Bootstrap method is known as a statistical methodology for estimating a population from data samples. In this study, the simulation data which been sampled are 50, 100 and 250 samples. This number been chosen due to the classification of the data set as small, medium, and large data set for this kind of case study. The data is simulated from Gaussian, Gamma and Poisson Distributions with mean value of 3.0 and standard deviation value of 0.5, where based on the sentiment analysis data. In this research, the data is divided into 80% for training data set and 20% for testing data set.

The model deployment for this research is considered as future research where model could be developed into a dashboard or system that can be used by any consumers which related with the study scope.

4. Results and Discussion

In this section, the results from GLM and machine learning approaches are discussed. Table 1 shows a comparison of the value of the AIC and *p*-value among the three GLM for different sample sizes and distributions. Generally, based on Table 1, different distributions and sample size give different significant products. However, we could see that the GLM using Gamma distribution shows advertising (advert1) is significant factor for 50 and 100 sample size. GLM using Gaussian distribution shows product is a significant factor for sample size of 100 and 250, which in line with the theory whereas the number of sample size increase, the factor tends to be significant. Based on Table 1, the result shown by the *p*-value are also represented by the AIC values.

Table 1
Comparison values of AIC and P-Value of the three Model

Sample Size	Type of Model	AIC	*p*-Value	Level of Significance	Factor/Variable
50	Gaussian	103.33	0.384		connect1
	Gamma	91.393	0.00906	**	advert1
	Poisson	158.46	0.5844		connect1
100	Gaussian	181.54	0.0243	*	product1
	Gamma	192.52	0.0433	*	advert1
	Poisson	304.84	0.7502		inno1
250	Gaussian	435.25	0.0207	**	product1
	Gamma	495.86	0.831		product1
	Poisson	742.6	0.624		brand1

Table 2 to Table 4 show results for k-Nearest Neighbors (KNN), Support Vector Machine (SVM) and Random Forest (RF) model. Table 2 shows the machine learning prediction error rates coefficient of determination result for 50sample size of Gamma Distribution. The error rates of MAE and RMSE show that KNN model has the lowest mean compared to other models, while SVM model has the highest coefficient of determination (R-squared) compared to KNN and RF models.

Table 2
Machine Learning Prediction Error Rates for 50 Sample of Gamma Distribution

Models: knn, svm, rf						
Number of resamples: 10						
			MAE			
	Min.	1st Qu	Media n	Mean	3rd Qu.	Max.
knn	0.6219	0.7039	0.9072	0.9168	0.9513	1.4792
svm	0.6108	0.7278	0.9614	0.9363	1.0113	1.4648
rf	0.4610	0.7966	0.9529	0.9315	1.0931	1.4095
			RMSE			
	Min.	1st Qu	Media n	Mean	3rd Qu.	Max.
knn	0.7161	0.8601	1.0554	1.0574	1.1020	1.6250
svm	0.7312	0.8419	1.1072	1.0864	1.1417	1.6128
rf	0.5687	0.8869	1.0935	1.0807	1.2130	1.5160
			Rsquared			
	Min.	1st Qu	Media n	Mean	3rd Qu.	Max.
knn	0.0008	0.0528	0.1478	0.2454	0.4796	0.5522
svm	0.0018	0.1337	0.3288	0.3994	0.6653	0.9465
rf	0.0001	0.0846	0.2620	0.2911	0.4034	0.9369

Table 3 shows the machine learning prediction error rates coefficient of determination result for 100 sample size of Gaussian Distribution. The error rates of MAE and RMSE shows that KNN model has the lowest mean compared to other models, while KNN model also has the highest coefficient of determination (R-squared) compared to SVM and RF models. Hence, this makes KNN model as the most accurate model to be tested in this research.

Table 3
Machine Learning Prediction Error Rates for 100 Sample of Gaussian Distribution

Models: knn, svm, rf						
Number of resamples: 10						
			MAE			
	Min.	1st Qu	Media n	Mean	3rd Qu.	Max.
knn	0.7471	0.8671	0.9917	1.0053	1.1568	1.2354
svm	0.8058	0.8862	1.0561	1.0188	1.1300	1.2067
rf	0.7994	0.9313	1.1022	1.0567	1.1379	1.3641
			RMSE			
	Min.	1st Qu	Media n	Mean	3rd Qu.	Max.
knn	0.8584	1.0283	1.1410	1.1400	1.2875	1.3567
svm	0.9108	1.0190	1.1962	1.1500	1.2644	1.3202
rf	1.0325	1.1089	1.2619	1.2202	1.2826	1.4599
			Rsquared			
	Min.	1st Qu	Media n	Mean	3rd Qu.	Max.
knn	0.0002	0.0348	0.1984	0.1806	0.2228	0.5619
svm	0.0002	0.0083	0.0752	0.1542	0.2321	0.5510
rf	0.0000	0.0090	0.1046	0.1263	0.1679	0.5152

Table 4 shows the machine learning prediction error rates and coefficient of determination result for 100 sample size of Gamma Distribution. The result of MAE rates shows the SVM model has the lowest rate while for RMSE shows that KNN model has the lowest mean compared to another model, while SVM model has the highest coefficient of determination (R-squared) compared to KNN and RF models.

Table 4
Machine Learning Prediction Error Rates for 250 Sample of Gamma Distribution

Models: knn, svm, rf						
Number of resamples: 10						
MAE						
	Min.	1st Qu	Media n	Mean	3rd Qu.	Max.
knn	0.7588	0.8462	0.9069	0.9049	0.9619	1.0317
svm	0.7766	0.8151	0.8955	0.8905	0.9327	1.0399
rf	0.6923	0.9117	0.9430	0.9225	0.9639	1.0731
RMSE						
	Min.	1st Qu	Media n	Mean	3rd Qu.	Max.
knn	0.9030	0.9839	1.0588	1.0532	1.1194	1.1798
svm	0.9264	0.9625	1.0598	1.0584	1.1358	1.2002
rf	0.9135	1.0487	1.0929	1.0823	1.1220	1.2404
Rsquared						
	Min.	1st Qu	Media n	Mean	3rd Qu.	Max.
knn	0.0005	0.0113	0.0321	0.0689	0.1085	0.2417
svm	0.0019	0.0081	0.0550	0.0843	0.1204	0.2547
rf	0.0007	0.0044	0.0133	0.0274	0.0277	0.1497

Table 5 shows the significant factor that has been recorded from the analysis. There are four significant factors that recorded *p*-value less than 0.05, the four variables are considered as significant factors for the business model. The significant factors are advertising and production variables. Based on Table 5, the least AIC value is considered as the most accurate regression model that fits the data. Hence, the Gaussian model is the most fit model to test for this research since Gaussian model has the lowest AIC value compared to another model.

Table 5
The overall significant results for the GLM and Machine Learning approach

Sample Size	GLM with Distribution	Machine Learning Method	Significant Factor	AIC
50	Gamma	KNN	advert1	91.393
100	Gaussian	KNN	product1, advert1	181.54
250	Gaussian	SVM	product1	435.25

5. Conclusions

To conclude, the advertising factor and production factor are the core competitive factor for the digital product in the digital businesses. The business provider should tackle this factor to generate more sales in the future. With the help of the analysis, this research validates that GLM can help digital service provider identify the significant factor to the business user. Hence, it is believed that the result of this research could help digital service provider increase their sales by analysing the significant service provided that is required by the business user. As a result, this research has discovered two significant factors in taking business user interest for purchasing the Telecommunication Company digital service.

Other than the factor which been identified to be considered by the Telecommunication Company to focus on, the sample size and different distribution considered in this research also give a guide to the academician in future result. As known, that, as the sample size increases, the model tends to be fitted good by using Gaussian distribution. It is recommended that for future research, researcher should consider bigger sample size and different type of distributions, so that the accuracy of the fit model is more accurately.

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