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IMPACT OF PREDICTIVE ANALYTICS IN BUSINESS WORLD

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Abstract - By the emergence and development of the new technologies in economy, the level of competition raised several times faster than the previous periods. Companies are facing the challenge of diminishing the production costs on high quality goods by implementing the modern technology in production, management, marketing, sales and all the other fields of the product realization. This paper is based on wide literature review and researched the latest virtual world business model tools, such as Virtual and Augmented Reality, the ways of using them in modern economy. I also investigated the patterns of different companies that applied for these technologies and their results. I introduced the main features of virtual world, and explored major technology waves that are Augmented Reality, Virtual Reality, and USEMIR (Ubiquitous Sensory Mixed Reality). Under the concrete examples, monetization of the virtual world business models had been explained to the readers. The main direction of my essay was introducing the previous precedents of technology implementation in macroeconomic level, its gains, challenges and future perspectives. Article revealed the strong relatedness between the Virtual World and Real-World Economies. It will be used on conducting surveys for first research. Moreover, readers can get the initial knowledge on the topic and the patterns that previously were investigated.

keywords - INNOVATION, ADAPTATION, TECHNOLOGY, NEW ECONOMY, TECHNOLOGY AND COMPETITIVENESS. CLASSIFICATION PRODUCTION MANAGEMENT USEMIR (UBIQUITOUS SENSORY MIXED REALITY)

INTRODUCTION

What is the status of analytics in your organization? If we are talking about predictive analytics that describe what has already occurred (e.g., dashboards and scorecards), you are probably pretty far along. If, on the other hand, we are discussing predictive analytics that forecast what will occur (e.g., regression analysis, neural networks) or prescriptive analytics that help determine what should occur (e.g., mathematical programming), you may have pockets of use, but overall, your enterprise may not be far along the maturity curve. We will refer to predictive and prescriptive analytics as advanced analytics. In some enterprises, advanced analytics is moving from being a “nice-to-have” feature to a requirement for competing in the marketplace. Such enterprises are analytics-based organizations. For example, think of large online retailers such as Amazon.com and Overstock.com that depend on advanced analytics for demand forecasting, pricing, dynamic display of product recommendations,customer segmentation analysis, campaign management, customer lifetime value analysis, and more. Other companies turn to advanced analytics to seize market opportunities. For example, Harrah’s (now a part of Caesars Entertainment) became an industry leader by using advanced analytics to better understand its customers’ gaming preferences and to offer them attractive incentives to play at its properties. Here is growing evidence that companies prosper from using advanced analytics. Management Review study found that top-performing companies in their industries are much more likely to use analytics rather than intuition across the widest range of possible decisions. A 2011 academic study revealed that firms that adopt data-driven decision advanced analytics Business He is a Fellow of TDWI and senior editor of the Business Intelligence Journal advanced analytics making have output and productivity that is 5 to 6 percent higher than what would be expected given their other investments and IT usage; in addition, there is a positive relationship of these measures with other performance measures such as asset utilization, return on equity, and market value. her evidence is clear that many firms will and should employ advanced analytics. his questions are—what does it take to become a successful analytics-based organization. Day by day people are getting addicted to virtual world's WEB life, i.e., social networking sites like Facebook, twitter or blogs etc. People are very eager to upload their life events –through pictures or through comments. This new lifestyle has become a common trend among people of all age groups. But in the midst of this venture, a new scope for intelligent analysis that is growing day by day is nothing else but our "DATA". Data Analytics, a recent research trend deals with the above issue and captures meaningful insights from this data which can create value. In the recent era, consumers have been remarkably quick to adopt trends and developments. Due to the changes occurring in social, political, and technological environments, opinion of public has been changing rapidly. This is why it is now crucial to identify and follow the early waves in the consumer ocean. Trend analysis is a structural mapping of expected changes in the behaviour of societies, markets, and the consumers who drive them. Trends tend to develop within different time frames and on different levels. They can be short term, medium term or long term. Trend analysis gives companies the opportunity to innovate with less stress Finding significant trends from large data sets has variety of applications. In this system, monthly retail sales data of US Census Bureau is analysed for 13 different NAICS retail trade categories. This data is analyzed for linear and SVM model and their performances are compared. Also, the search trend data available on Google trends2 is collected and mapped to these categories. Effect of Google search on market is analyzed and compared using linear and SVM model.

Financial forecasting is an integral part of business planning most events that affects business are unpredictable however most of the forecasting in this context is used to guide the decision which are taken for the business position at the peninsular and explicating Trends for these forecasts to hold true for the given business then need to be practical and realistic to the facility this existing financial statement are used as a map

1.1 PROFIT AND LOSS FORECASTING

Forecasting profit during a short time frame like for a spam of 12 years is extremely important to understanding the business and planning ahead the entire process to finding out estimates of variables indicating business performance using the values of the variables from the prior or previous periods allows the business to not just identify but also modified possible glitches in the operations of the business and does avoid any sort of major financial crisis or problems given that some of the future estimates of the variables do not a dear to expectations for Casting profits and loss gifts by per values for the revenues and the expenses that are begin expected by the business over a certain frame of time it shows likely amount of revenue to be accurate from the current and thus forecasted level of trendingProducing a profit or loss for Casting is not a picture of liquidity since it contains a lot of times which are not cash like depreciation or creditors that have not been paid orthe involves that have been created and raised but the cash do have not been accrued or produced it does not include the payment of any loans.

Ayush Profit and Loss Forecast							
	January	**February**	**March**	**April**	**May**	**June**	**July**
Sales Revenue	**10,000**	**10,000**	**10,000**	**10,000**	**10,000**	**8,000**	**8,000**
Variable costs	4,500	4,500	4,500	4,500	4,500	4,500	4,500
Gross Profit	**5,500**	**5,500**	**5,500**	**5,500**	**5,500**	**4,400**	**4,400**
Fixed Costs							
Rent	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Labour	4,000	4,000	4,000	4,000	4,000	4,000	4,000
Utilities	100	100	100	100	100	100	100
Phone	30	30	30	30	30	30	30
Insurance	100	100	100	100	100	100	100
Advertising	40	40	40	40	40	40	40
Accounting	130	130	130	130	130	130	130
Miscellaneous	100	100	100	100	100	100	100
Total Fixed Costs	**5,500**	**5,500**	**5,500**	**5,500**	**5,500**	**5,500**	**5,500**
Net Profit (Loss)	**0**	**0**	**0**	**0**	**0**	**-1,100**	**-1,100**

2. BEHAVIOURAL MARKETING

The base of a successful business or organization is its reach to the targeted consumers. With effective and efficient marketing strategies, a business could bloom to its highestlevels. With the marketing for the business reaching to its desired public, proper strategic analysis needs to be done so as to make the business reach to the target audience. This is where the behavioural marketing comes into play. Consumers are targetedon the basis of the websites they consume or searches for a commodity. This data is analyzed for patterns to predict the audience to be notified of the organization. The data is collectively organized and analyzed to gather the targeted audience and the marketing is done in the form of advertisements shown particularly to the category of audience for which the business being marketed could be useful. It provides the marketer with the ability to get in touch with the desire segment of the society hence. Leading to a well thought and effective marketing in turn making the business bloom.

3. BUSINESS FUTURE PERSPECTIVE

Data analysis can inevitably predict the future of the business keeping in mind the current scenarios. It helps the business in taking effective measurements that could possibly lead to the better future of the organization. With proper analysis, decision making abilities are provided to the organization and could lead to a perspective growth of its business. With the market trend changing rapidly, the trend of the changes that would be of impact to the business can be predicted efficiently and measures could be taken in handling those impacts. With strategic analysis, certain crucial decision points could be handled within an organization so as to achieve a foreseen goal of the organization.

1.4 DATA ANALYTICS

Predictive analytics comprises of varied statistical trends andtechniques ranging from machine learning and predictivemodelling to data mining to efficiently analyse the historicaldata and information so as to process them to createpredictions about the unknown future. As perthe business aspect of predictive analytics, predictiveanalytics help in exploiting the patterns found in thehistorical business data to identify the risks andopportunities. It captures the relationships betweenvarious factors to provide the assessment of risk or apotential threat and help guide the business throughimportant decision-making steps. Predictive analytics is sometimes described in reference to predictive modellingand forecasting. Predictive analytics is confined to thefollowing three model that outlines the techniques forforecasting.

1.5 PREDICTIVE MODELS

1. Predictive models are the models that define the relationship between the various attributes or features of that unit. This model is used to assess the similarities between a group of units providing assurance of the presence of similar attributes being exhibited by a group of similar units.Plotting the data has shown us that the number of cycles checked out per day is showing a lot of fluctuations. There are some emergent patterns that are coming into light, for instance, the number of cycles taken out during the summer months are higher as compared to the winter months.

	Model 4		Model 5		Model 6		Model 7	
	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.
$\gamma 00$ = Intercept	7.26***	0.30	7.26***	0.32	8.64***	0.60	8.69***	0.57
γ_{10} = Coefficient of d	−0.09	0.10	−0.09	0.12	−0.47*	0.21	−0.51***	0.14
γ_{20} = Coefficient of d^2	−0.05***	0.01	−0.05***	0.01	−0.06**	0.02	−0.05***	0.01
γ_{01} = Coefficient of u					−0.28**	0.11	−0.29**	0.10
γ_{11} = Coefficient of d:u					0.08*	0.04	0.09***	0.02
γ_{21} = Coefficient of u:d^2					0.00	0.00		
AIC	2076.96		2076.73		2066.84		2064.90	
BIC	2106.73		2119.27		2109.37		2103.18	
Deviance	2063.0		2056.7		2046.8		2046.9	
Residual df	513		510		510		511	
Number of level-1 observation	520		520		520		520	
Number of level-2 clusters	52		52		52		52	
$\tau_0^2 = \mathrm{var}(U_{0i})$	3.40		3.90		2.82		2.82	
$\tau_1^2 = \mathrm{var}(U_{1i})$	0.19		0.41		0.14		0.14	
$\tau_2^2 = \mathrm{var}(U_{2i})$			0.00					
$\sigma_e^2 = Var(\epsilon_{ij})$	2.24		2.07		2.24		2.24	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; d, dimension; u, individual differences variable; U_{0i}, random intercept effect; U_{1i}, random slope effect of dimension; U_{2i}, random slope effect of quadratic dimension; ϵ_{ij}, level-1 residuals.

1.1 DESCRIPTIVE MODELS

Descriptive models are the models that identify and quantify the relationshipsbetween the various attributes or features of theunit which is then used to classify them into groups.It is different from the predictive model in the abilityto compare and predict on the basis ofrelationshipbetween multiple behaviours of the units rather thana single behaviour as is done in the predictive models.

	M	p	S^2	SD	p
Agency experiences					
Intercept	2.69	< .001	0.53	0.73	< .001
Change	−0.05	< .01	0.51	0.71	< .001
Ideology experiences					
Intercept	2.20	< .001	0.35	0.59	< .001
Change	−0.07	< .01	0.33	0.57	< .001
Prosocial behaviors					
Intercept	3.22	< .001	0.22	0.47	< .001
Change	0.07	< .001	0.15	0.39	< .001

1.1DECISION MODELS

Decision models are the models that identify and describe the relationship among allof thevaried data elements present that includes theknown data set upon which the model is to bedefined, the decision structure that is defined forclassification and categorization of the known dataset as well asthe forecasted or predicted result seton the application of decision tree on the known.

Step	Problem Solving	Stage	Decision Making
1	Identify the problem	1	Frame the decision
2	Explore alternatives	2	Innovate to address needs and identify alternatives
3	Select an alternative	3	Decide and commit to act
4	Implement the solution	4	Manage consequences
5	Evaluate the situation	4 & 1	Manage consequences and frame the related decisions

PERSONNEL WITH ADVANCED ANALYTICAL SKILLS

Advanced analytics requires three skills: knowledge of the business domain, the ability to work with large amounts of data, and modelling skills. he typical business analyst is strong in the first two areas but doesn't have advanced modelling skills (e.g., multivariate analysis). With proper training, some business analysts may be able to accept the advanced analytics challenge, at least for more structured analytics (such as customer segmentation analysis)when supported by appropriate software.

THE RIGHT ANALYTICAL TOOLS

Most organizations' BI environments support descriptive BI. Although traditional BI vendors may claim their tools support data mining and predictive analytics, this is not always the case. Slicing/dicing and data visualization are not data mining. Having said this, traditional BI tools and predictive analytics are highly synergistic. For example, BI tools are useful in understanding the data and thinking about relationships before using predictive analytics, and data visualization tools are useful for interpreting the output from models. Data mining requires tools that incorporate algorithms and processes designed specifically hidden relationships in data. SAS and SPSS are two of the traditional leaders in this space. R is a programming language and software environment for statistical computing and graphics and is now the most popular tool used by data miners. It is also at the core of many open-source products. Many modelers like to work with open-source products or experiment with new ones. Although you may want to standardize on a single product or a few products, modelers will often have preferences for specific tools (perhaps ones they learned in school) or those that are well suited for specific tasks.

CONCLUSION

There are many requirements for using predictive analytics or becoming an analytics-based organization. If you are not ready to commit yet but have a business need, you might consider outsourcing some of the work. For example, companies such as Revenue Analytics, Mu Sigma, and Method Care (formerly Apollo Data Technologies) provide predictive and prescriptive modelling services. Companies that choose to take this approach don't have to invest as much time and money in developing in-house capabilities. Of course, some may not feel comfortable turning their data over to a third-party provider, and it can get expensive if there is considerable analytics work to be done.A track of early signals or trends helps organizations to be prepared for any events that may occur in future. Proper analysis will yield proper outcomes, and while performing analysis, web search data has always turned out to be useful. The idea of using Google's search query data for predictive analytics turned out to be a successful indicator for accurate predictions. From the experimental results, we can infer that SVM model is better as it was observed that prediction errors are small in case of SVM compared to linear model. Also, while performing prediction, if Google trends data were added then prediction errors were lower for most of the months, as compared to predicting without Google Trends query index. Based on our work as well as the current state-of-the-art, the horizon can be expanded. Different other sub categories can also be included in combination with the above-mentioned categories to check their impact. Also, the model can be tried with different tuning parameters to obtain more accurate result.

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