Michel CALCIU Associate Professor IAE Business School, University Lille1 104 Av. Du Peuple Belge 59000 Lille tel: +33(0)320123409 e-mail: <u>Michel.calciu@univ-lille1.fr</u>

# Browser based marketing decision support for consuming RESTful statistical web services. An application to Customer Value Calculations

### Abstract:

Low building productivity and lack of communication between marketing scientists and managers are the two main obstacles to the diffusion of Marketing Decision Support Systems (MDSS). The approach that we introduce in this paper, that is based on latest IT developments, suggests probably the quickest way to overcome both obstacles and to accelerate access of marketing models to the market. It allows marketing scientists to solve managerial problems instantly by consuming statistical web services and to deliver them as actionable MDSS using only client-side (browser) web technologies that nowadays offer enhanced user interaction and experience. An illustration is given for a collection of Customer Value Calculation Models built as statistical packages.

#### Introduction

The slow of diffusion of Marketing Decision Support Systems (MDSS) is as a long dating leitmotif in marketing literature (Little, 1970,2004; Eliashberg & Lilien, 1993; Lilien & Rangaswamy, 2000,2008; Lilien, 2011). Low building productivity and lack of communication between marketing scientists and managers apear as the two main obstacles. *Evolution of the web towards increased consumer experience:* The web has come to a historical stage where web based decision support applications have won the battle against desktop ones. MDSS, in order to be used, must integrate these breakthrough developments in both, front-end or client-side and back-end or server-side web technologies.



Figure 1 – Evolution of Web browser technologies

*Source: http://www.evolutionoftheweb.com/* 

Although we agree with Tim Berners Lee<sup>1</sup>, the inventor of the Web, that terms like Web 2.0 can be described as jargon, we will use the "buzzwords" Web 1.0, Web 2.0 and Web 3.0 in order to distinguish the period before the year 2000, the one between 2000 and 2009 and the one after 2009 in figure 1. The first period corresponds to a "static" web that essentially was

<sup>&</sup>lt;sup>1</sup> http://en.wikipedia.org/wiki/Web\_2.0#cite\_note-developerWorks\_Interviews: \_Tim\_Berners-Lee-4, Retrieved 2012-08-26.

an extension of hypertext and hypermedia concepts to the Internet. In the second period the "dynamic" html or HTML4 evolved together with server side technologies in order to transform the web into a computing platform serving web applications to end-users. The last period, that began after the launch of Google's Chrome browser, often labeled as the "semantic web", besides the diffusion of XML standards through which documents "make sense" to machines and not only to humans, has witnessed an explosion of web services whose consumption induced the need to substantially enhance user experience through a multitude of client-side or browser technologies that gravitate around the emerging HTML5 standard.

*Embedding models as web services:* Lilien and Rangaswamy (2000, 2008) distinguish marketing modeling applications as to their degree of visibility and integration. According to this classification, models can be visible or embedded and standalone or integrated. Web services deal with embedded models, be they standalone or integrated pieces of software. Embedded distributed applications can be accessed over the network at a lower level through RPC (Remote Procedure Calls) and at a higher level as Web services. The latter provide envelopes that make such applications "universally" discoverable, able to communicate and interact with over the network. By making marketing modeling applications interoperable over the "net", web services help satisfy recurring desiderata in academic literature dealing with democratization (Little, 1991), automation (Bucklin, Lehman & Little, 1998) and diffusion (Little 2004, Lilien 2011) of Marketing Decision Support Systems (MDSS)

Web services are self-contained, self-describing, modular applications that can be published, located, and invoked across the Web. They can easily integrate with other services, from the same or different companies, to create a complete business process. This interoperability allows to dynamically publish, discover and bind a range of Web services through the Internet. The following standards play key roles in Web services: Universal Description, Discovery and Integration (UDDI), Web Services Description Language (WSDL), Web Services Inspection Language (WSIL), Simple Object Access Protocol (SOAP). They constitute together with some additional technologies such as WS-Addressing, WS-ReliableMessaging, WS- Security the "Big" Web services technology stack (Pautasso & al., 2008, Richardson & Ruby, 2007) that defines the WS-\* standard.

This WS-\* standard came under criticism as to its presumed complexity. The alternative REST (Representational State Transfer) solution takes its inspiration from the web itself and shows that the same principles that have made the success of the World Wide Web can be used to solve enterprise application integration problems and to simplify service-oriented architectures. MDSS are aimed to integrate as enterprise applications and can therefore benefit form such technological trends.

REST is a style of software architecture for distributed systems such as the World Wide Web. The WWW itself is probably the largest implementation of REST principles. REST was introduced and defined in his doctoral thesis by Roy Fielding (2000), one of the principal authors of the Hypertext Transfer Protocol (HTTP) specification (Fielding & Tailor, 2002). A service is considered "RESTful" if conforming to REST principles. RESTful Web services are gaining increased attention because of their publishing and consumption simplicity (Vinowski, 2002).

This paper introduces an approach, based upon latest IT developments, that allows marketing scientists to solve managerial problems instantly by consuming Restful statistical web services and to deliver them as actionable MDSS using only client-side (browser) web technologies that nowadays offer enhanced user interaction and experience. An illustration is given for a collection of Customer Value Calculation Models built as a statistical package.

# RESTful web service implementation of a statistical system

There is a very recent and promising initiative to turn statistical computing into a RESTful web service. It is part of a doctoral research project in applied statistics called "open computing" or OpenCPU (Ooms, 2011). OpenCPU, whose first stable version (1.0) has just been released (August 2013), opens up the R statistical software as a REST style service over the Internet. R is unique as it is open-source and backed by a professional and experienced team (called the r-core group) as well as a huge community of users from both academics and industry (Ooms, 2011). It has a reliable general functional computing language and regroups specialized packages for almost any scientific field. In accordance with REST philosophy OpenCPU uses HTTP vocabulary (GET and POST) in order to expose and use statistical objects and functions from R.

Service discoverability: Service discoverability is obtained using GET together with URIs. The URI "<u>ocpu/library</u>/" lists available statistical packages in R. When packages are URI endpoints, objects and functions available in those packages are listed. When objects or functions are endpoints, mime-types (output formats) that can be used to render those objects are exposed. The syntax GET with ocpu/library/[package name]/R/[object name]/[output format] for example "<u>ocpu/library/stats/R/lm/ascii</u>" exposes the linear regression (lm) function that is available in the stats package.

Service use: While GET reads a resource, POST executes R scripts and functions. POST with URIs creates resources (objects, graphics, files, etc). In order to execute the above mentioned function with appropriate arguments the URI and query-string would be "ocpu/library/stats/R/lm/json?formula=speed~dist&data=cars"

where parameter *formula* indicates the causal relationship between dependent and independent variables and parameter *data* indicates the data set (here cars) where those variables can be found.

Coping with statelessness: As, like HTTP, REST is stateless, if a subsequent function (like summary or plot) needs to be applied to the output object, a double step request could be used. If successful, a POST request returns a response indicating the location of where to retrieve results from the execution. In a first step the previous command without the "json" endpoint would place the resulting objects in the ocpu/tmp directory with a unique name (hashkey). The second step would then apply the subsequent function (summary) to the saved object using a POST request with /ocpu/library/base/R/summary?object= [hashkey]. More detailed and highly illustrative information can be found at https://public.opencpu.org/.

# Customer Value calculation models embedded as a web service

The application we open up as a RESTful service, regroups several models that have been classified by Jain and Singh (2002) as Customer Lifetime Value (CLV) calculation models. They are integrated by us as R packages and organized using three classification criteria: dynamic customer behavior contexts (contractual, non-contractual), transaction occasion's chronology aspects (discrete and continuous time) and customer heterogeneity (deterministic and stochastic models).

For deterministic models two packages for discrete transaction occasions have been developed: one for the contractual context the so-called retention model (ltvret) and one for the non-contractual migration model (ltvmigr).

Stochastic models, unlike the deterministic ones, take into account customer heterogeneity. They are regrouped in one package (ltvmstochastic) that covers both discrete and continuous buying occasions contexts. The models and their authors are given in table 1.

Table 1 - Stochastic Models for various dynamic customer behavior contexts

CUCTOMER	Contractual	Shifted Betageometric ( <b>sBGD</b> - Fader & Hardie, 2007); Beta-discrete-Weibull (BdWD - Fader & Hardie, 2010)	<i>Exponential Gamma</i> (EGD or Pareto Distribution of second kind)
RELATION- SHIP	Non- contractual	I- tractualBetageometricBetabinomial BetageometricPareto & Co /NBDbeta-Bernoulli & Shang, 2010)Beta/Bernoulli (BG/BBD - Fader, Hardie All, 200Pareto & Co /NBD	<b>Pareto/NBD</b> (Schmittlein, Morrison & Colombo, 1978 <i>Betageometric</i> / <i>NBD</i> ( <b>BG/NBD</b> - Fader, Hardie & Lee, 2005); <i>Modified Betageometric</i> / <i>NBD</i> ( <b>MBG/NBD</b> - Batislam et al., 2007)
		Discrete	Continuous
		TRANSACTION OCCASIONS	

All packages contain polymorphic functions using arguments customer behavior data like

All packages contain polymorphic functions using arguments customer behavior data like purchase recency and/or frequency in order calculate log-likelihood, purchase probabilities, probabilities of being active (noted Pactive, only for non-contractual contexts), expected transactions (ET, noted eYt), discounted expected transactions (DET) and CLV for a given lifetime or for the long term.

*Discovering services:* Giving the package name as an endpoint all available functions and objects can be discovered from the mnemonic notations that include the name of the model (here ParetoNBD) and the polymorphic functions mentioned before.

Method->URI	GET -> /ocpu/library/ltvmstochastic/R
Output	"paretonbdcov_ll","paretonbd_det","paretonbd_eXt","paretonbd_eYt","paretonbd_ _ll","paretonbd_lXt","paretonbd_Pactive"

Functions or objects of the package can be exposed in various formats. Some are adapted to human- others to machine discovery. For *human discovery* the ascii format can be used (as for the linear model before) as well as several help formats like text, html or pdf. The later can be seen in the two examples below

(Method) Endpoint	GET <a href="https://www.gencommunications.com">/ocpu/library/ltvmstochastic/R/bgnbd_Pactive/help/text</a>
Output	<pre> Description: Performs BGNBD Probability of being active in a future period of length t for an individual with past observed behavior (X=x,tx,T) E[P(active at T x,t_x,T, r, alpha,a,b)]=\frac 1 {1+delta {x&gt;0}\frac a {x+b-1} &lt;=ft( \frac {alpha + T} {alpha + t x}\right)^{{r+x}}</pre>

(Method) Endpoint	GET <a href="https://ccpu/library/ltvmstochastic/R/bgnbd_Pactive/help/pdf">/ccpu/library/ltvmstochastic/R/bgnbd_Pactive/help/pdf</a>
Output	<b>Description</b> Performs BGNBD Probability of being active in a future period of length t for an individual with past observed behavior (X=x,tx,T) $E[P(activeatT x, t_x, T, r, \alpha, a, b)] = \frac{1}{1 + \delta_{x>0} \frac{a}{x+b-1} \left(\frac{\alpha+T}{\alpha+t_x}\right)^{r+x}}$

The json format is preferred for *machine discovery* as the arguments of the functions appear distinctly and are well documented as shown in the example below.

(Method) Endpoint	GET <a href="https://ccpu/library/ltvmstochastic/R/bgnbd_Pactive/help/json">/ccpu/library/ltvmstochastic/R/bgnbd_Pactive/help/json</a>
Output	<pre>[ "arguments" :[{ "name" : "param","description" : "a vector with initial values for the four parameters that need to be estimated (a,b,r and alpha)"},{"name" : "x","description" : "number of repeat purchases (frequency)"},{"name" : "t_x","description" : "time of last purchase (recency)"},{"name" : "T","description" : "time since first purchase (anciency)"}]</pre>

*Using services:* HTTP's POST method is used to call functions or objects. In the example below the probability of being active is calculated for a customer during 6 successive periods.

$\begin{array}{ll} (\text{Method}) & \rightarrow \\ \text{URI} \end{array}$	POST         /ocpu/library/ltvmstochastic/R/bgnbd_Pactive/json?param=[0.242,           4.413,0.792,2.425]&x=[1,1,1,2,2,2]&t_x=[35,35,35,38,38,38]&T=[39,40,41,42,43,44]
Output	[0.7306891,0.7250844,0.7195351,0.7792473,0.7709142,0.7625433]

From the recency  $(t_x)$ , frequency (x) and anciency (T) one can see that a purchase occurred in period 4 having as a result an increase of the probability of being active. Here both the arguments of the function and the output use the JSON format.

#### Browser based MDSS for consuming RESTful statistical web services.

We consider that a MDSS is strictly browser based when it consists only of static web pages that is HTML documents with their eventual "natural" complements Cascadind Style Sheets (css) and Javascript (js) files. Naturally such MDSS "live" within browsers and depend entirely on browser capabilities.

OpenCPU suggests two kinds of browser based decision support tools, a generic one that allows to explore the web service (see figure 2) and a framework to build problem specific decision support (see figure 3). Both use Twitter Bootstrap, a free framework for creating websites that contains HTML and CSS-based design templates that provide modern appearance for typography, tables, form elements, navigation and other interface components. Several JavaScript components are included as jQuery plugins. It supports responsive design meaning that the layout of web pages adjusts dynamically to the characteristics of the device used (PC, tablet, mobile phone). With Bootstrap and jQuery many newer browser technologies evoked in figure 1 are included, like Ajax, DOM traversal and manipulation, event handling, animation etc. They contribute to an enhanced user experience.

The *generic decision support* allows adding or removing parameters and files. HTTP methods can be selected and URI endpoints can be edited in order to explore statistical service requests. Figure 2 illustrates the use of the generic tool to compute customer probabilities of being active from the last example of the previous section.

					0.7794
Method	Endpoint			1	0.7627
POST -	/ocpu/library	/ltvmstochastic/R/bgnbd_Pactive/json		· · ·	
Method and End	looint are requ	ured. Click below to add additional parameters.			
Parameter Name	e	Parameter Value			
param		[0.242, 4.413,0.792,2.425]	× [		
x		[1,1,1,2,2,2]	) ×		
t_x		[35,35,35,38,38,38]	× [		
т		[39,40,41,42,43,44]	× [		

Figure 2 – Generic decision support to explore the statistical web service

MDSS has been defined as a "coordinated collection of data, systems, tools, and techniques with supporting software and hardware by which an organisation gathers and interprets

relevant information from business and environment and turns it into a basis for marketing action" (Little, 1979, p.11). In other words it is a collection of means to assist the decision maker in solving a specific managerial problem (Evrard, Pras & Roux ,1997).

A Problem specific MDSS as the one presented in figure 3, can be easily build by using the Applications Framework of OpenCPU. Briefly explained a problem specific application in OpenCPU is an R package that contains a www directory with static web pages (html, css, js). The package contains R functions that will be called by those web pages through some wrapper JavaScript functions that address the web service. By convention, these applications are placed in the /inst/www/ directory of the R source package.

The marketing scientist who is supposed to have good knowledge of the statistical system of his choice, in this case R, should be able to create an R function that produces a plot like the one in figure 3 and automatically generate a package around it. If for example the function is called "myfunction" the package source can be generated by the R command package.skeleton(list=c("myfunction"), name = "adhocpackage"). To transform the function into a web application as the one in figure 3 it is necessary to populate the /inst/www/ directory in the package source by adapting content from existing opencpu web aplications that are freely available.



The MDSS in figure 3, computes and displays (plots) the customers' probability of being active for one of the three models (see table 1) that are adapted for situations characterized by non-contractual customer relationship with continuous purchase occasions. Each model has been previously calibrated on data. The decision maker selects the model and indicates the number of periods and customers for which to perform calculations based on given or simulated purchase incidence data. As can be observed from the plot the probability of being active reaches its maximum after each repurchase and falls more or less rapidly in the time intervals with no purchase incidence depending on each customer's purchase recency and frequency. Such a MDSS can help the managers find some probability levels that signal customer departure intentions and trigger some customer win back policies.

#### **Conclusion and discussions**

In this paper we recognize, paradigmatic changes in web technologies that can change the way MDSS are built and used.

We argue that the web is in a new era, sometimes labeled web 3.0, that began somewhere after the launch of Google's Chrome browser at the end 2008. It is characterized by the explosion of web services and important developments of browser or client-side technologies (see figure 1). The latter facilitate the consumption of such services by offering enhanced user experience. This evolution offers a nice opportunity to marketing scientists to bring their MDSS to the market. For a marketing scientist, there is no easier and quicker way to create a MDSS than by executing commands on a statistical system opened up as a web service and by organizing interaction with a user-friendly web browser based interface. This can

substantially reduce the two main obstacles to the adoption of marketing models by managers: the lack of productivity and communicability.

Therefore we introduce OpenCPU, a very recent initiative to open the statistical system R as a RESTful web service whose first stable (official) version has just been released (August, 2013). It is part of an ongoing doctoral research (Ooms, 2011) that, in our opinion, substantially contributes to democratize statistical computing. We illustrate this new approach for building MDSS with customer value calculation models gathered by us in an R package.

Besides contributing packages that regroup several customer value calculation models to the R statistical system, this research shows how to implement MDSS applications that consume RESTful web services. Web services, a major breakthrough in distributed computing, have as to our knowledge very rarely been discussed and never been implemented in marketing MMDSS literature.

Our purpose is to keep marketing scientist updated with new technologies affecting both statistical computing and model based decision support systems and insist on technological breakthroughs that can accelerate adoption of marketing models and their access to the market.

We think that this approach is probably the best adapted to most marketing scientists who have normally good knowledge in statistics but poor knowledge of modern programming and IT. Most marketing scientists have rather advanced skills with the statistical system they use. Many of them can express their models as a sequence of commands (code snippets). Eventually, if aware of automated package generation facilities, they could be able to produce, adhoc, a problem specific package that integrates the MDSS as a web application like the one we have called "adhocpackage" in the previous section. If the marketing scientist doesn't feel comfortable with producing the web application and only produces the statistical package, the access to the market of the models that are implemented in that package is no longer the marketing scientist's problem. As services they can get discovered and used over the Internet. Intermediaries, in the sense of Lilien (2011), can take the torch and prepare models for managerial use.

Of course browser based MDSS are not new (see Calciu & Salerno,1997) although visual and semantic browser capabilities have tremendously increased (especially after 2008), but the combination with statistical web services is very new. It can be extremely powerful and offer actionable solutions to real world marketing problems. An important advantage of browser based MDSS is that they are integrated and "live" anywhere within web pages in this way "decision supportive documents" may be produced that can be highly illustrative and play an important role in the pedagogy and diffusion of marketing models.

An eventual limitation of this approach is that at this point OpenCPU is not necessarily prepared for dealing with 'big data'. It does not scale beyond what R itself scales to. But R itself is already a key player in the "big data" business so that there is hope to see in near future that OpenCPU or another web service solution for R to become able to offer solutions for such situations.

#### References

Batislam, E. P., Denizel M, and Filiztekin A.(2007), Empirical Validation and Comparison of Models for Customer Base Analysis, *International Journal of Research in Marketing*, 24 (September), 201–209.

Bucklin, R.E., Lehman, D.R. and Little, J.D.C. (1998), From Decision Support to Decision Automation: A 2020 Vision, *Marketing Letters*, 9, 3, 235-246.

Calciu M., Salerno F. (1997), Modélisation participative sur le WEB. Un modèle de rétention des clients, *Décisions Marketing*, No. 11, Mai - Août

Eliasberg, J., Lilien, G.L, Eds. (1993), *Handbook in Operational Research and Management Science*, Vol.5: Marketing, Elsevier Science Publishers B.V, Amsterdam: North Holland.

Evrard, Y., Pras, B., Roux, E. (1997), Market - Etudes et recherches en marketing : fondements, méthodes, Nathan, Paris

Fader P.S., Hardie B. G. S. and Berger P. D. (2004), Customer-Base Analysis with Discrete-Time Transaction Data, unpublished working paper

Fader P.S., Hardie B.G. S. and Lee K.L. (2005), "Counting Your Customers" the Easy Way: An Alternative to the Pareto/NBD Model, *Marketing Science*, 24 (Spring), 275–284.

Fader P.S, Hardie B.G.S. (2007) How to project customer retention, *Journal of Interactive Marketing*, 21, 1, 76-90

Fader, P.S., Hardie B.G. S. (2010), Customer-Base Valuation in a Contractual Setting: The Perils of Ignoring Heterogeneity. *Marketing Science*, Vol. 29, 1, 85–93

Fader, Hardie, and Shang: Customer-Base Analysis in a Discrete-Time Noncontractual Setting. *Marketing Science*, 29,6, 1086–1108

Fielding, R.T. (2000), Architectural Styles and the Design of Network-based Software Architectures, Doctoral dissertation, University of California, Irvine

Fielding, R.T.; Taylor, R.N. (2002), Principled Design of the Modern Web Architecture (PDF), ACM Transactions on Internet Technology (TOIT) (New York: Association for

Computing Machinery) 2 (2)n, Mai: 115-150, doi:10.1145/514183.514185, ISSN 1533-5399

Jain D., Singh, S.S., (2002). Customer Lifetime Value Research in Marketing. A Review and Future Directions. *Journal of Interactive Marketing*, 16(2), 34-46

Lilien G.L., Rangaswamy A. (2000), Modeled to bits: Decision models for the digital, networked economy, Intern. J. of Research in Marketing, 17, 227–235

Lilien, G.L., Rangaswamy, A. (2008), Marketing Engineering: Connecting Models with Practice, in *Handbook of Marketing Decision Models*, B. Wierenga, ed. New York: Elsevier Press, 527–60.

Lilien, G.L. (2011), Bridging the Academic–Practitioner Divide in Marketing Decision Models, *Journal of Marketing*, 75 (July), 196–210

Little, John D.C. (1970), Model and Managers: The Concept of a Decision Calculus. *Management Science*, Vol. 16, No. 8 (April), 467-485

Little, John D.C. (1979), Decision Support Systems for Marketing Managers, *Journal of Marketing*, Vol. 43, no. 3 (Summer), pp.9-27.

Little, J.D.C. (1991), Operations Research in Industry: New Opportunities in a Changing World, Operations Research, 39 (July/August), 53I42.

Little, J.D.C. (2004), Comments on Models and Managers: The Concept of a Decision Calculus, Management Science, 50 (12), 1841–61.

Ooms, J.C.L. (2011) Open Computing: Challenges and Opportunities. Phd. Proposal Draft. UCLA Dept. of Statistics, December

Richardson, L.; Ruby, S. (2007), RESTful Web Services, O'Reilly, ISBN 978-0-596-52926-0

Ooms, J.C.L. (2011) Open Computing: Challenges and Opportunities. Phd. Proposal Draft. UCLA Dept. of Statistics, December

Pautasso, C., Zimmermann, O., Leymann, F. (2008), RESTful Web Services vs. Big Web Services: Making the Right Architectural Decision, *17th International World Wide Web Conference (WWW2008)*, Beijing, April

Schmittlein D.C., Morrison D.G., Colombo R. (1987), Counting Your Customers: Who They Are and What Will They Do Next?, *Management Science*, 33 (January), 1-24.

Vinoski, S. (2002), Putting the "Web" into Web services: Interaction models, part 2. *IEEE Internet Computing*, 6(4):90–92, July.