Technical Paper
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Big Data Analytics

Benchmarking SAS®, R, and Mahout

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Accurate and Simple Analysis of Big Data

The amount of data created, and potentially collected, every day by the interactions of individuals with their computers, GPS devices, cell phones, social media, medical devices, and other sources has been termed "big data." Analysis of big data is especially needed in predictive modeling, which often uses a large number of observations and predictor variables to predict a binary response that represents an individual's predicted future behavior. SAS customers want to analyze big data, particularly in the form of predictive modeling, accurately and easily.

This paper describes a benchmark study of various scenarios that are created by applying three classification algorithms in two SAS products and two open-source products to model four classification problems from real customers. The algorithms are logistic regression, decision trees, and a random forest algorithm that is based on Random Forest (Breiman 2001). The products that were benchmarked are SAS® Rapid Predictive Modeler for SAS® Enterprise Miner™, SAS® High-Performance Analytics Server (using Hadoop), and two-open source software packages: R (R Core Team 2012) and Apache Mahout (Apache Software Foundation 2012). Each scenario was evaluated for model quality, overall completeness, and overall effort required by the modeler. Each of the SAS and open-source products showed strengths and limitations, which are described in the section "Results."

Data

This benchmark study performs classification modeling on real customer data sets that are summarized in Table 1. To maintain confidentiality of customers, only approximations are given for the data.

Table 1: Description of Scenario Data

Industry **(Prediction)**	**Number of Observations**	**Number of Predictor Variables**	**Event Rate***	**Notes**
Marketing (response to campaigns)	350,000+	1000+	2%	Individual-level information is scarce; large quantity of neighborhood- and district-level data. Very low rate of target outcome has presented modeling difficulties.
Entertainment (involuntary attrition by using a churn model)	1,500,000+	100+	6%	Rich set of subscription, billing, demographic, and technical support data.
Financial (response to offered services)	400,000+	30+	8%, 18%	Smallest data set, but large blocks of missing data; target was already oversampled.

Telecom (response to contact with customers)	2,000,000+	450+	8%	Data were expanded 60-fold from the original source and are less difficult to model.

** Event rate is the percentage of targets that corresponds to the event (that is, for binary targets, this is the proportion of '1' to all outcomes).*

Benchmark Objectives and Methods

The objectives of this benchmark study are to evaluate the following:

- Model quality
- Overall completeness
- Overall effort required by the modeler to develop a final scoring model

To evaluate these criteria, each of the algorithms was fit in each software product and pre-specified outcome criteria were recorded.

Three methods were selected to build models: logistic regression, decision tree, and random forest. In order to directly compare the modeling results from the software and algorithms, parameters were chosen consistently across software. For example, random forests were created in each product with 60% of the training data for each tree, and 100 trees were created.

To enable direct comparison, the data were split into training and validation sets through SAS Enterprise Miner High-Performance Analytics nodes rather than splitting the data in individual software packages (where random starting seeds would vary the training data sets). The data were split into a 60/40 training and validation partition, stratified on the target. These data sets were then used as the training and validation sets for Mahout and R. However, these data sets could not be used directly as the training and validation sets for SAS Rapid Predictive Modeler for SAS Enterprise Miner because it automatically oversamples the training data if the event level is less than 10%. Therefore, the training and validation sets were assessed on the Rapid Predictive Modeler for SAS Enterprise Miner model after the model was developed. Thus, although the Rapid Predictive Modeler for SAS Enterprise Miner creates the model slightly differently, the numerical results it reported are from the model that is applied to the same data sets and can be compared to results from SAS High-Performance Analytics Server, Mahout, and R.

The four software packages were run on machines that are comparable to machines that real-life analysts might have access to when they use each type of software. Measuring the scalability of the vendor algorithms is not a fair comparison, particularly because SAS High-Performance Analytics Server was already configured on a much larger massively parallel processing (MPP) appliance. Table 2 shows the general setup for each software platform.

Table 2: Description of Operating Environment

Software	Type	Appliance	Available RAM
SAS High-Performance Analytics Server 12.1 (using Hadoop); SAS Enterprise Miner 12.1 client	SAS product	Greenplum; two master hosts with 60 nodes	96 GB each
Rapid Predictive Modeler for SAS Enterprise Miner and SAS Enterprise Miner 12.1, SAS 9.3	SAS product	Microsoft Windows 2008 R2 server	21 GB
R 2.15.1 “Roasted Marshmallows” version (64-bit)	Open source	Microsoft Windows 2008 R2 server	15 GB
Mahout 0.7	Open source	Five-machine Hadoop cluster	48GB each

Model Quality

Model quality was assessed through common model quality measures (Han and Kamber 2006): cumulative lift in the first decile, percentage of correctly classified events (called event precision), and overall percentage of correct classification. Standardized training and validation data sets stratified by the target were used across the model test suite.

Overall Completeness

To assess overall completeness of the software algorithms, a sample of popular requests from SAS customers were collected and an attempt was made to incorporate the predictive modeling algorithms into the software packages.

Neither SAS High-Performance Analytics Server nor Mahout includes decision tree algorithms. (SAS High-Performance Analytics Server plans to release support for in-memory decision trees in June 2013.) In the case of Mahout, a random forest with one tree and 100% of the data was created to simulate a decision tree. In SAS High-Performance Analytics Server, a neural network was used to provide an additional algorithm for comparison. A direct comparison of neural networks was not possible because Mahout does not implement a neural network algorithm.

Overall Modeler Effort

Overall effort required by the modeler was calculated by recording the time required to manually prepare and model the data and the time required to run the procedure as a proxy for overall ease of use and effort. Longer times to prepare the data for analysis and build the scoring models were considered indicators of increased modeler effort. Further, only preexisting software algorithms were used for each scenario to evaluate the goals of the project. For example, R uses the change in Akaike’s information criteria (AIC) when it evaluates variable importance in stepwise logistic regression whereas SAS products use a change in Wald’s χ^2 as the default. Although it would be possible to write functions in R to make a stepwise logistic procedure that is comparable to the procedures implemented in SAS products, doing so would defeat the goal of looking at completeness. Theoretically, any algorithm could be programmed into R by using R script, into Mahout by using Java, or into SAS by using the IML procedures, a DATA step, or a SAS macro. Because a goal of this benchmark is to control for programming knowledge, any additional programming that was needed to carry out an algorithm was not performed and not included in the modeler effort considerations. Therefore, the study used only packages that are currently available in R and only the command-line interface in Mahout. No user-defined extensions were applied to either SAS High-Performance Analytics Server or Rapid Predictive Modeler for SAS Enterprise Miner models.

Results

Results of the benchmark study indicate the following overall findings:

- The types and depth of classification models that could be run in SAS products and R outnumbered the options for Mahout.
- However, the object-oriented programming in R led to memory-management problems that did not occur in SAS products and Mahout; thus, the size of customer data that could be analyzed in R was considerably limited.
- When the customer modeling scenarios were evaluated based on event precision and rank ordering, SAS High-Performance Analytics Server models were more accurate.
- The overall misclassification rate was comparable across software in most instances.
- The effort required by individual modelers to prepare a representative table of results was much greater in both R and Mahout than it was in SAS High-Performance Analytics Server and SAS Rapid Predictive Modeler for SAS Enterprise Miner.

The following sections describe findings of the study in each of its objectives.

Overall Completeness

Table 3 indicates how completely each software package fit each class of models. A red “x” indicates that the software cannot fit this class of models, and a green check indicates that it can.

Table 3: Completeness of Vendor Software for Predictive Modeling

Model	**Mahout**	**R**	**SAS High-Performance Analytics Server**	**SAS Rapid Predictive Modeler for SAS Enterprise Miner**
Decision tree	✗	✓	✗	✓
Random forest	✓	✓	✓	✗
Stepwise logistic	✗	✓	✓	✓
Neural network	✗	✓	✓	✓

Continuous response (Y)	✗	✓	✓	✓
Ensembles/Model Combining	✗	✗	✗	✓

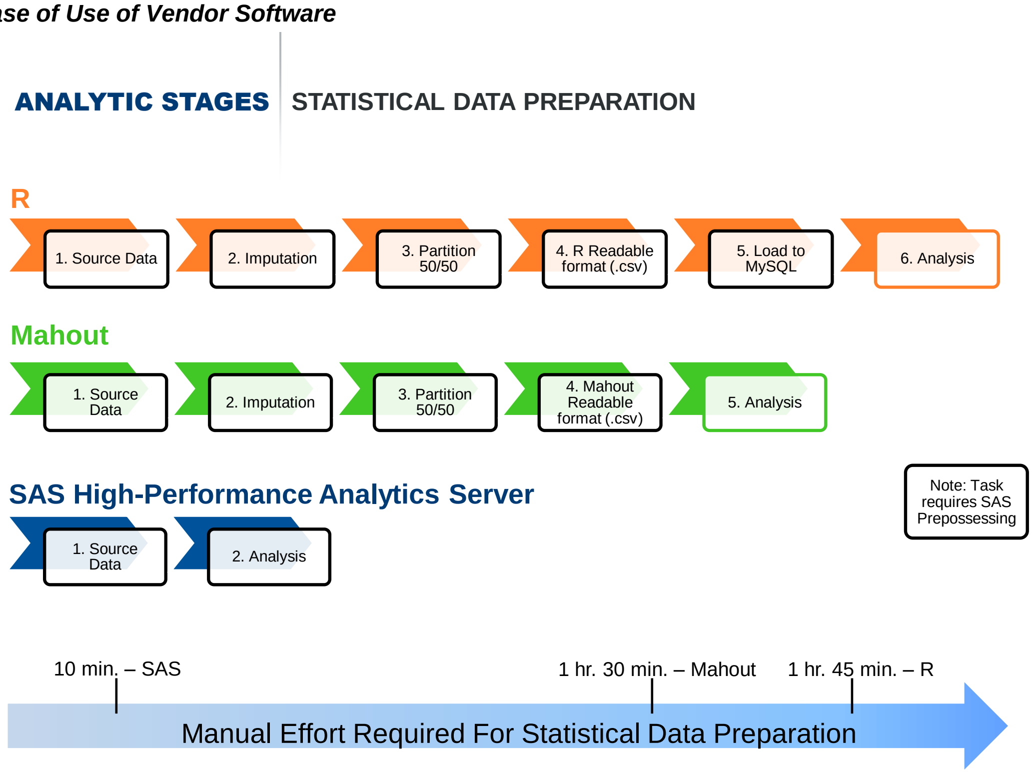
Because of the limitations shown in Table 3, the following alternative analyses were performed: a full model logistic regression and a random forest with one tree were performed in Mahout, and multilayer perceptron neural networks in lieu of decision trees were fit in SAS High-Performance Analytics Server. The R packages used were randomForest (Liaw & Wiener, 2002) for the Random Forest algorithm, rpart (Therneau & Atkinson, 2011) for the decision tree algorithm, and glm (R Core Team, 2012) for logistic regression.

Another desirable feature of the SAS products is the large number of model evaluation statistics that are available beyond the percentage that are correctly classified from a confusion matrix. These statistics for evaluating model quality are implemented in annotated graphical output to make interpretation easier. Getting these statistics from both Mahout and R would require further programming. In addition, although R has typically been recognized as having flexible graphical features, the R packages used in this paper do not have many of the same built-in plots as the SAS products and would need to be programmed by hand.

Overall Modeler Effort

Figure 1 demonstrates that SAS products are easier to use than the open-source software. A significant amount of manual data preparation is required before any analysis can be done in R or Mahout.

Figure 1: Ease of Use of Vendor Software



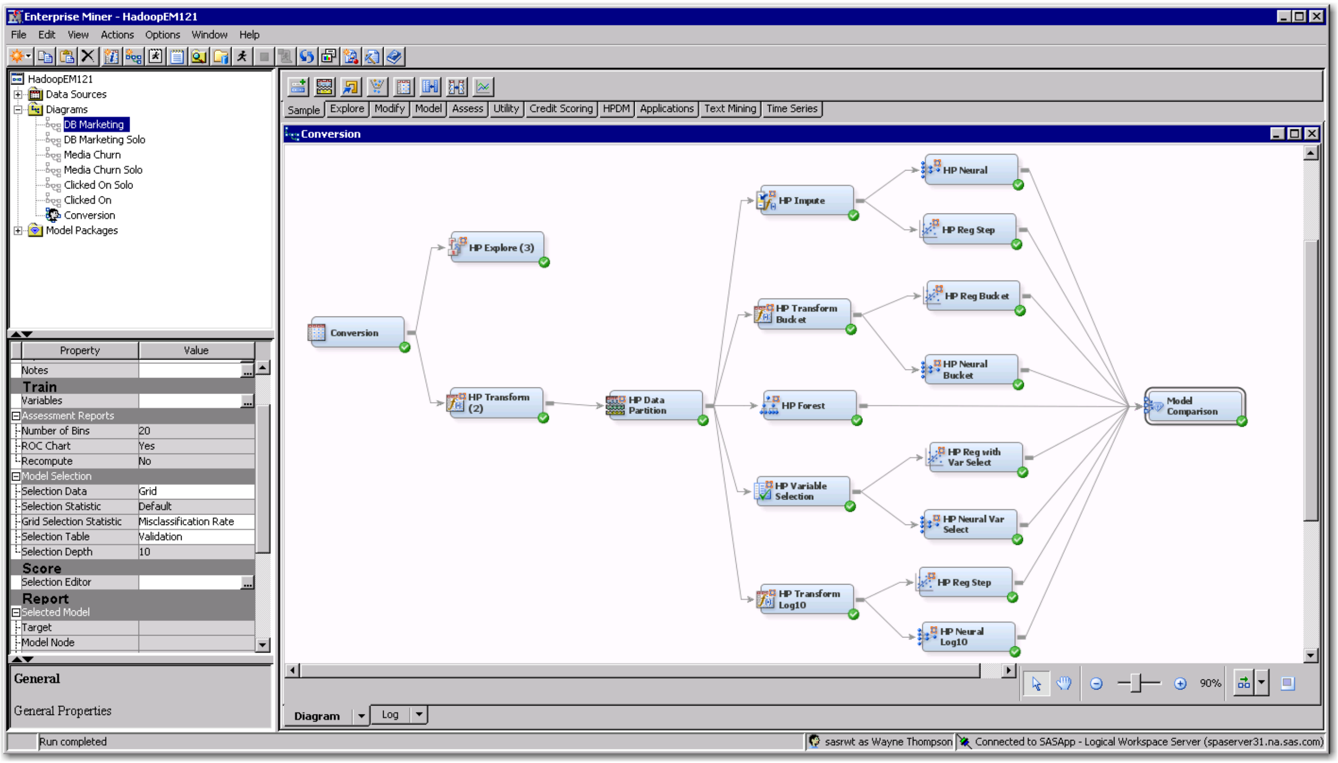
The differences in ease of use have several causes. The following list describes the factors that affect ease of use of the various software packages:

- Because Mahout does not have built-in methods to handle missing data, the modeler first needs to prepare any statistical data outside of Mahout. For these scenarios, the data preparation included variable selection, imputation, and dropping observations with large portions of missing data while dropping as few variables and observations as possible. Mahout cannot perform these actions because it lacks imputation and data manipulation capabilities. These preparation steps were instead performed using Base SAS® 9.3. The remaining data was modeled in Mahout, while each dropped observation was treated as a non-event.

- Similarly, when data are read into R, missing values must be designated as "NA" in the original data. One package in R, the randomForest package (Liaw and Wiener 2002) does provide imputation tools, but the original data set must be formatted with the previously mentioned "NA" values. Before the original data set was read into R in this benchmark, it was coded in Base SAS 9.3. R uses object-oriented programming, a programming paradigm that uses "objects" and their interactions to design applications and programs. Each object that results from modeling the big data is stored in memory, unless it is expressly removed by the modeler. These objects can grow to be as big as, if not larger than, the original data. To avoid holding both the big data and the objects, first the data had to be loaded into a MySQL database and then called from R by using the RMySQL package (James and DebRoy 2012). Loading the data into MySQL was also done in Base SAS 9.3.
  In addition, R was limited in how much data it could process. Bewerunge (2011) found that R could not model a data set larger than 1.3 GB because of the object-oriented programming environment within R. In this study the two largest data sets (marketing and entertainment) had to be systematically reduced in order to obtain any results in R. Beginning with the complete data set (100%), the data set was reduced by 10% until a manageable data set could be run. The reduction was done by stratified sampling in order to preserve the original event rate.

- SAS High-Performance Analytics Server provides a full spectrum of tools to partition the data, impute missing values, apply statistical transformations, preselect features, and evaluate models. The SAS Enterprise Miner High-Performance Analytics process flow diagram, shown in Figure 2, dramatically shortens iterative model development effort and is self-documenting. Once a model flow was built for a scenario, it was reused for the other analysis scenarios via an XML diagram exchange. The advanced advisor feature saves considerable time by automatically assigning variables to metadata roles (such as measurement level) and rejecting variables that exceed a missing value threshold or exceed a certain number of discrete values. A modeler can override any of the assigned settings.

Figure 2: SAS Enterprise Miner High-Performance Analytics Model Diagram



- SAS Rapid Predictive Modeler for SAS Enterprise Miner is the easiest of all tools that require the user to only specify the target variable. Rapid Predictive Modeler for SAS Enterprise Miner automatically treats the data to handle outliers, missing values, skewed data, collinearity, variable selection, and model selection. Further, SAS Rapid Predictive Modeler for SAS Enterprise Miner automatically oversamples rare target events and uses inverse priors for the classification cutoff.

Model Quality

Table 4 and Table 5 compare the model quality for two scenarios. In both tables, the double asterisk in Table 4 identifies the top-performing model in terms of the model quality criterion (event precision), and “NR” indicates that the software does not report the information and that additional programming would be required to obtain the results. Table 6 presents summaries of the top models for all the scenarios.

Table 4 shows that the top-performing model in the purchased financial services scenario is the SAS High-Performance Analytics Server stepwise logistic regression model. It provided the largest percentage of correctly classified targets, more than twice as high as Mahout’s logistic regression. R does not provide information about the percentage of correctly classified events; further programming would be required to obtain this information. Mahout ran a full model, with all predictors that were not dropped during variable selection, rather than a stepwise variable selection procedure. SAS High-Performance Analytics Server ran a stepwise logistic regression, effectively eliminating predictors that do not relate to target prediction.

Table 4: Model Quality Comparison for Purchased Financial Services

Software	Model	Percentage of Correctly Classified Events Training	Cumulative Lift 10%	Percentage of Correctly Classified Events Validation	Cumulative Lift 10%
Mahout	Logistic regression	16.06	NR	15.80	NR
	Random forest	0.10	NR	0.07	NR
	Random forest with one tree	1.52	NR	0.93	NR
R	Logistic regression	NR	NR	NR	NR
	Random forest	0.80	NR	0.87	NR
	Decision tree	21.56	NR	22.87	NR
SAS High-Performance Analytics Server	Logistic regression**	34.96	2.30	34.95	2.33
	Random forest	29.01	2.26	29.01	2.28
	Neural network	28.98	2.32	28.98	2.32
SAS Rapid Predictive Modeler for SAS Enterprise Miner		3.01	2.31	3.08	2.32

Table 5 shows that the top-performing model in the entertainment scenario is the SAS Rapid Predictive Modeling model.

Table 5: Model Quality Comparison for Entertainment Media Churn

Software	Model	Percentage of Correctly Classified Events Training	Cumulative Lift 10%	Percentage of Correctly Classified Events Validation	Cumulative Lift 10%
Mahout	Logistic	4.88	NR	4.88	NR

	regression				
	Random forest	6.31	NR	5.83	NR
	Random forest with one tree	7.03	NR	5.58	NR
R	Logistic regression				
	Random forest		Insufficient	Memory	
	Decision tree				
SAS High-Performance Analytics Server	Logistic regression	23.62	6.67	23.62	6.67
	Random forest	22.18	6.46	22.18	6.48
	Neural network	22.20	6.67	22.20	6.67
SAS Rapid Predictive Modeler for SAS Enterprise Miner **		42.56	6.16	42.46	6.17

Table 6 shows which overall models performed best based on event precision. For the entertainment scenario, SAS Rapid Predictive Modeler for SAS Enterprise Miner provided a model that far outperformed the other modeling software. The next closest model was SAS High-Performance Analytics Server logistic regression with only 23.62% correct classification. The financial services data was most accurately classified for both target event rates by using SAS High-Performance Analytics Server logistic regression. This brief snapshot shows that in three of the four modeling scenarios, SAS products provided better model quality as it relates to the statistics of lift and event classification rate. One interesting note is that Mahout and R arrived at some null models in which all predictions were classified as non-events. Thus, the modeling of rare events within R and Mahout was considerably more difficult than in the SAS products.

Table 6: Best Overall Models by Validation Event Precision

Scenario	**Best Product (Algorithm)**	**Percentage of Correctly Classified Events** **Training**	**Cumulative Lift 10%**	**Percentage of Correctly Classified Events** **Validation**	**Cumulative Lift 10%**
Marketing	SAS Rapid Predictive Modeler for SAS Enterprise Miner	5.68	1.26	5.23	1.26

Entertainment	SAS Rapid Predictive Modeler for SAS Enterprise Miner	42.56	6.16	42.50	5.24
Financial with 18% target event rate (see also Table 4)	SAS High-Performance Analytics Server (logistic regression)	34.96	2.30	34.95	2.33
Financial with 8% target event rate	SAS High-Performance Analytics Server (logistic regression)	12.77	2.03	12.77	2.03
Telecom	SAS Rapid Predictive Modeler for SAS Enterprise Miner	70.21	8.12	70.23	8.12

Discussion

Why do the SAS products produce better models? SAS Rapid Predictive Modeler for SAS Enterprise Miner can take a subsample of the data in which the target event is oversampled before the model is created. In addition, Rapid Predictive Modeler for SAS Enterprise Miner uses a variety of variable selection model comparisons and ensembles/model-combining to create the best model. Even though the model is created on a subsample of the data, it continues to perform well when it is generalized to the entire training and validation sets. SAS Rapid Predictive Modeler for SAS Enterprise Miner also uses inverse priors as opposed to a 0.50 cutoff boundary. Because the events were rare for the modeling scenarios, Rapid Predictive Modeler for SAS Enterprise Miner can classify more of the events at a lower threshold.

In some cases, oversampling the target event and using inverse priors (as done by SAS Rapid Predictive Modeler for SAS Enterprise Miner) produced models that are far superior to the other methods, as seen in Table 5. In other cases, the same oversampling and use of priors produced models inferior to the SAS High-Performance Analytics Server methods, as seen in Table 4. Further investigation is needed to separate the effects of oversampling from the use of priors and to resolve when the use of priors and oversampling is an effective tool.

SAS High-Performance Analytics Server contains methods for imputation and variable selection, which are not available in Mahout or R. Imputing a priori and variable selection in SAS lead to higher-quality data being used for SAS High-Performance Analytics Server models, which in turn lead to models that have a higher event precision. In addition, Mahout has no built-in stepwise logistic regression. Thus the models run in this instance were saturated models in Mahout; that is, the models included all variables in the data set. From a parsimony argument, including all the variables does not produce the most efficient or best-fitting model. Some statistical communities prefer LASSO feature selection over more greedy stepwise methods. Only SAS High-Performance Analytics Server and R support LASSO regression.

Conclusions and Next Steps

Results were compared in terms of model quality, modeler effort, scalability, and completeness. Assessing by event precision reveals that the SAS High-Performance Analytics Server models had the best predictive modeling quality. SAS products and R offered more completeness than Mahout in the types and depth of classification models that can be run. However, R was less scalable because the object-oriented programming in R led to memory-management problems that did not occur in SAS products and Mahout. Thus, the size of customer data that could be analyzed in R was severely limited. The modeler effort required to prepare data for actual modeling in R and Mahout was much greater than for the two SAS products. The clear leader in requiring the least modeler effort was SAS Rapid Predictive Modeler for SAS Enterprise Miner.

Although there is no definitive answer regarding which software package is “best” for customer predictive modeling, this study has uncovered several areas of strengths in addition to some limitations for all the products. From the customer standpoint (rather than from a development kit perspective), the SAS products provide the most complete and easy-to-use tools for predictive modeling. But comparing the software packages for only one purpose does not present a complete picture. Mahout has been developed as a development kit, not necessarily a final product for use by the private sector. The open-source nature of both R and Mahout allows for a wider range of programming functionality than in the SAS products. SAS recognizes the use of such a kit and is currently developing a node in Enterprise Miner that can use R script to further expand the breadth of functionality available in SAS Enterprise Miner.

The software packages were implemented in different environments, each with different amounts of available RAM, as shown in Table 2. A next step in the benchmark process is to investigate scalability and timing.

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