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## Factorization Machines, Visual Analytics, and Personalized Marketing

Suneel Grover, Advisory Solutions Architect, SAS Institute Inc. and Professorial Lecturer,  
The George Washington University (Department of Decision Science - School of Business)

### ABSTRACT

Competition in customer experience management has never been as challenging as it is now. Customers spend more money in aggregate, but less per brand. The average size of a single purchase has decreased, partly because competitive offers are just one click away. Predicting offer relevance to potential (and existing) customers plays a key role in segmentation strategies, increasing macro- and micro-conversion rates, and the average order size. This session (and the associated white paper) covers the following topics: factorization machines and how they support personalized marketing; how SAS<sup>®</sup> Visual Data Mining and Machine Learning, SAS<sup>®</sup> Decision Manager, and SAS<sup>®</sup> Customer Intelligence 360 support building and deploying factorization machines with digital experiences; and a step-by-step demonstration and business use case for the sas.com bookstore.

### INTRODUCTION

**Why does your organization's website or mobile app exist? What are you hoping to accomplish with your business by being digital? What are the most important priorities for your digital presence?**

Here are three goals that most organizations share:

- Sell more stuff.
- Make marketing more effective.
- Delight customers.

**Goals are specific strategies leveraged to accomplish business objectives. Let's walk through one of the examples cited above.**

*What does sell more stuff actually mean?*

- Do x (more cross-sell or upsell efforts).
- Improve y (increase conversion rates).
- Reduce z (reduce abandon cart rates).

Every brand offers a digital experience for a reason (for example, **if you've ever used Amazon or Netflix, you've experienced the value of recommendation systems firsthand**). These sophisticated systems identify recommendations autonomously for individual users based on past purchases and searches, as well as other behaviors. Customers get algorithmically produced recommendations on additional offerings that are intended to be relevant, valued, and helpful. Consumers can use recommendations to do the following:

- Find things that are interesting or useful.
- Narrow a set of choices.

- Explore options.
- Discover new things.

Marketers can benefit from recommendation systems to enhance offers that proactively build better customer relationships, retention, and sales. For example, organizations typically realize the following:

- Higher engagement, click-through, and conversion rates.
- New opportunities for promotion, persuasion, and profitability.
- Deeper knowledge about customers.

Recommendation systems aim to address the customer-centric paradigm that considers the different actions **that a brand can take for a specific individual and decides on the “best” offering (such as one or multiple products)**. The goal is to produce an offer or proposition **determined by the customer’s interests, and the organization’s objectives and policies**. This is well suited for the following:

- Inbound real-time interactions, like websites, mobile apps, or call centers.
- Outbound scheduled or triggered interactions, like email or SMS text messages.

How are recommendation systems different from other forms of analytically-driven one-to-one marketing<sup>1</sup> (excluding rule-driven targeting)? **Let’s address this by defining** the following three tiers differentiated by data availability:

1. A/B, multi-arm bandit, or multivariate [testing](#)<sup>2</sup> – An extremely popular flavor of optimizing a digital experience that requires little data about the visitor to get started.
2. Recommendations – Interactions can be grouped and compared, allowing you to identify aspects of behavior that act as proxies for interests. Light to moderate amounts of data are required.
3. Propensity [modeling](#)<sup>3</sup> – Predictive targeting based on probabilistic likelihoods using machine learning. Typically requires more data, such as behavior, history, location, demographics, and psychographics.

Before diving into the nuts and bolts of analytical approaches for recommendation system development, **let’s take a moment to consider the value proposition of [micro-moment marketing](#)**<sup>4</sup>.

The philosophy behind micro-moment marketing is that in the world today, consumers are bombarded by content, ads, offers, emails, texts, tweets, push notifications, and everything else imaginable. The industry has reached a point of “[content shock](#)”<sup>5</sup> where consumers cannot digest much more content. Whether you are walking down a city street, sitting in a coffee shop, attending a sporting event, or vacationing at a resort, look around. **What do you see? It’s stunning to observe the number of eyeballs viewing digital screens. In parallel, it isn’t a surprise that marketers venture to where audiences engage.** The question is the following:

*Do marketers need to adapt to capture the attention of consumers?*

It's important to objectively realize that your brand or product isn't the center of your consumer's world. In fact, most marketing-centric content is perceived as an interruption to a customer-oriented experience. The key of micro-moment marketing is to embrace the notion that a few seconds exist to capture the attention of your target. Within that tiny window, brands are challenged to convey a communication that resonates.

Ultimately, the customer journey is just an amalgamation of micro-moments across channels, devices, and varying flavors of intent. Sometimes these moments will be focused on content consumption, raising awareness, or seeking service, while other interactions are more purchase-driven.

Pivoting back to recommendation systems, the main intent here is to provide the following:

- Align with key business imperatives.
- Deliver through customer-interaction channels.
- Inform targeted offers.
- Shape multichannel conversations.

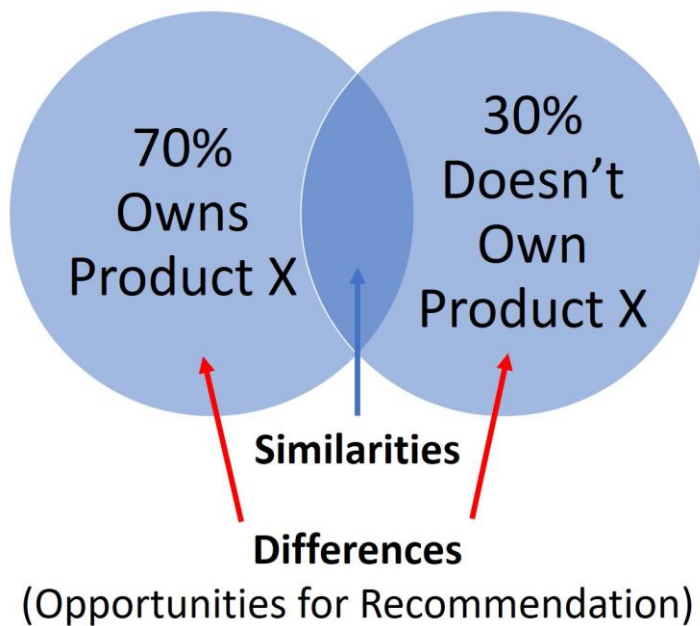
Recommendation systems are evolving, and the topic of predictive analytics, machine learning, and artificial intelligence is the headline. At the center of the conversation is the desire to embed analytics with rule-based constraints into customer experiences to provide the optimal treatment, one step, or decision, at a time. Brands desire integrating analytical scoring to improve arbitration processes for offer propositions during real-time interactions, or when triggering communications.

## **USER-CENTRIC VERSUS ITEM-CENTRIC FILTERING**

Marketers can use two flavors of algorithmic approaches to recommendations.

User-centric collaborative filtering is a very popular way of recommending products or content. It involves finding general similarities in behavior or characteristics between users then identifies specific differences between those linked users to make the case for sales opportunities.

For example, you might identify a group of customers who have purchased a common set of offerings. If 70 percent of a segment also have Product X, then you have a potential cross sell item for the 30 percent that have not bought it. The strength of the prediction for X (the filtering part) to a user depends on how similar that user is in behavior to others in the group (the collaborative part).



**Figure 1. User-centric Collaborative Filtering**

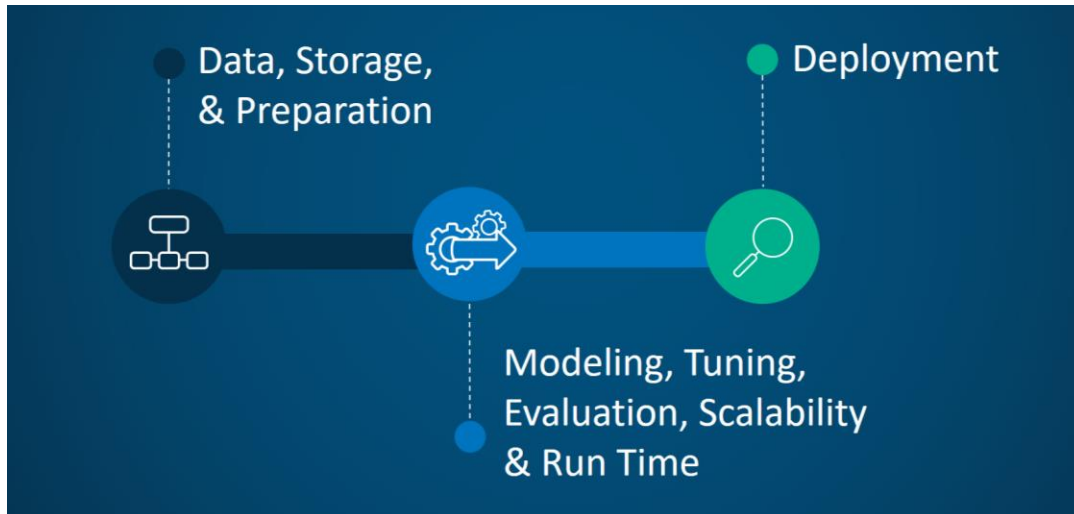
Item-centric (or content-based) filtering is used to recommend other products based on **associations**. This is helpful when you don't know anything about the user other than they are interested in a product in their current web or mobile session. Product X is associated with Products Y and Z. A popular example of this approach is called association rule learning<sup>6</sup>, which is a rule-based machine learning method for discovering relationships between variables. The association method is intended to identify strong rules discovered in data using measures of interestingness (support, confidence, and lift).

For example, the rule: {Cavaliers, Warriors} → {Wizards} found in the ticketing sales data of an NBA professional basketball organization generates a lift value of 3, indicating that if a fan has purchased tickets to see their local team play the Cavaliers and Warriors, they are three times as likely to have also bought a ticket to see the Wizards. Such information can be used as the basis for decisions about digital marketing activities such as promotional pricing, or targeted product recommendations.

## **MEASURING CONSUMER INTEREST IN PRODUCTS AND SERVICES**

Recommendation systems require more than just building statistical models. Measurement and deployment requires the following:

1. Collect data about users, items, and profiles.
2. Prepare, aggregate, and filter data for specific types of algorithms.
3. Run an algorithm or algorithms and produce actionable scoring.
4. Deliver personalized recommendations.



**Figure 2. Measurement and Deployment**

Before you do any analysis, you need data. To enable an algorithmic recommendation model from a user's behavior, a distinction is often made between explicit and implicit forms of data collection.

Examples of explicit data collection include asking a user to do the following:

- Rate an item on a sliding scale.
- Rank a collection of items from favorite to least favorite.
- Add to cart, add to wish list, and posting to social media
- Purchases

Examples of implicit data collection include the following:

- Observing the items that a user views on a website or app.
- Search for terms or brands.
- Analyzing item/user viewing times.
- Session duration, frequency of sessions, and homogeneity of product views (within or across categories)

A decision needs to be made here. For example, your brand selects an implicit data **collection method to capture a prospect's interest in a specific product**, offering, or piece of content. The simplest method is to measure whether a user views a product, and how many times. This can then be aggregated across website visits and/or app sessions. For each user and product, you end up with a count.

In reality, data is often highly skewed, with many visitors who viewed one product, or none. Plus, brands with multiple offerings might find that numerous products are never viewed. This is an example of the sparsity problem, and even the most active users of a website or app will have only viewed a small subset of the overall offerings.

Here are a few challenges every recommendation system must overcome:

**Scalability:** As a recommendations database grows, the performance decreases. It is beneficial to try to make systems that can handle large amounts of data and produce accurate recommendations quickly. There will always be a trade-off between performance and prediction accuracy; however, recent innovations in the parallelization of algorithm execution is addressing the challenge.

**Cold-start problem:** The problem appears at early stages of a recommender system's life cycle, or when a new user or item is added to the system. If there is little information about users or items, the collaborative filtering will behave poorly.

**Sparsity:** It is common in digital marketing for people to view, click, or purchase relatively few items compared with the total number of items available. This leads to a sparse users-items representation matrix and, therefore, inability to identify neighbors or derive common behavior patterns. The result is low-quality recommendations. This problem is addressed in latent factor modeling algorithms that use dimensionality reduction on items and users, resulting in the identification of common behavior patterns within a reduced dimensional space.

## INTRODUCTION TO FACTORIZATION MACHINES

According to Jorge Silva and Raymond E. Wright's [proceeding](#)<sup>7</sup> paper from SAS® Global Forum 2017, factorization models, which include factorization machines as a special case, are a:

*"Broad class of models popular in statistics and machine learning. For example, principal component analysis is a well known type of factorization model that has long been a staple of dimensionality reduction. Matrix factorization has been widely used in text analysis and recommender systems. More recently, [Rendle \(2010, 2012\)](#)<sup>8</sup> has proposed factorization machines for recommender systems and click-through rate prediction. Factorization machines are a powerful model that significantly extends matrix factorization."*

In other words, a factorization machine is a predictive model that combines features of a support vector machine<sup>9</sup> and matrix factorization<sup>10</sup>. By modeling all variable interactions with factorized parameters, factorization machines can handle large data with high volumes of missing values (that is, sparse data), as well as trained in linear time.

Factorization models have attracted a lot of research in the fields of intelligent information systems and [machine learning](#)<sup>11</sup>. They have shown excellent prediction capabilities in several important applications, such as personalized marketing and recommendation engines.

## HOW DO FACTORIZATION MACHINES SUPPORT PERSONALIZED MARKETING?

The algorithm aims to learn consumer preferences to recommend items such as movies, books, songs, or other types of offerings. The purpose is to predict how a user would react to a set of items, and then recommend items that the user is likely to prefer the most. Whether in real time while customers browse, or through outbound marketing later, several things need to happen.

1. At first, while learning about your users' tastes and preferences, recommendations can be based on item attributes alone.
2. Over time (and with enough data), factorization machines enable useful analysis to deliver more meaningful recommendations.
3. **Other users' inputs can improve the results, qualifying why the system should be retrained periodically.**

SAS Customer Intelligence 360 and SAS® Viya® provide an end-to-end solution, and the platform consists of the following:

- A scalable front end that records user interactions to collect, prepare, and store aggregated data that is analytically ready.
- Machine learning capabilities.
- Algorithms that can analyze and create relevant recommendations.
- Storage of user scoring that can be used by the deployment front end, in real time or later, based on the timeliness requirements for interactions.

## USE CASE: SAS BOOKSTORE

In this example, you will see how the [SAS bookstore](#) can use factorization machines to compute relevant recommendations and present them to customers who are browsing the **brand's website. With countless titles available, predicting how customers would rate books enables a personalization strategy to prioritize showing specific book titles that they are likely to be interested in.** For example, by knowing that customers are more likely to purchase a book with a rating higher than 4.5; therefore, we predict the rating and recommend books with ratings above 4.5.

SAS Customer Intelligence 360 can collect data about users based on the following:

- Implicit behavior.
- Explicit input.

For a bookstore, it is common for a subset of users to leave ratings. Outside of this specific use case, other proxies such as pageviews or screen views could serve as data inputs. However, in this example, users and items share a data trail that analysts can use to form a data-table matrix for modeling. Suppose you have user ratings of 1 - 5 where each value represents a rating given by the user.

	SAS® for Forecasting Time Series	The Little SAS® Book	Deep Learning for Numerical Applications with SAS®	An Introduction to SAS® University Edition
U1	5	3	–	1
U2	4	–	–	1
U3	1	1	–	5
U4	1	–	–	4
U5	–	1	5	4

**Figure 3. Input Data Set**

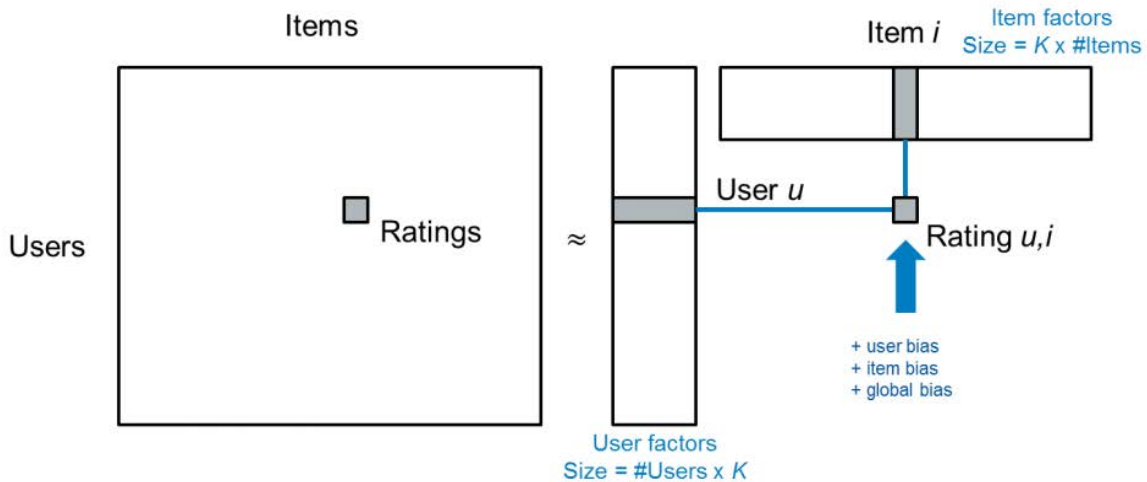
We observe from the table that some of the ratings are missing, and we would like to predict these. Ultimately, the following is our end goal:

	SAS® for Forecasting Time Series	The Little SAS® Book	Deep Learning for Numerical Applications with SAS®	An Introduction to SAS® University Edition
U1	4.98	2.98	2.17	0.99
U2	3.96	2.36	1.98	0.98
U3	1.03	0.94	5.33	4.96
U4	1.01	0.84	4.57	3.95
U5	1.35	1.06	4.91	4.11

**Figure 4. Analytically Scored Output Data Set**

Notice that you can closely re-create the existing ratings, as well as get an approximation to the missing values. The intuition behind using matrix factorization to solve this problem is that there should be some latent features that determine how a user rates a book. Based on your digital property's traffic volumes, this matrix can become very large, because there can be millions of users and product items. Moreover, it is sparsely observed, because typically only a small fraction of historical ratings is available for analysis.





**Figure 5. Matrix Factorization for a Recommender System. Users and Items Are Characterized by their Respective K-dimensional Factor Vectors.**

Users and items are characterized by their respective k-dimensional factor vectors. Revisiting Jorge Silva and Raymond E. Wright's research effort referenced earlier:

*"You can overcome these challenges by factoring the matrix into lower-dimensional user and item factors, which can be used to predict new ratings. For recommender systems, the input vector is typically constructed using binary indicator variables for user  $u$  and item  $i$ ."*

$$x = (0, \dots, 0, 1, 0, \dots, 0, 0, \dots, 0, 1, 0, \dots, 0)$$

$|U|$ 
 $|I|$

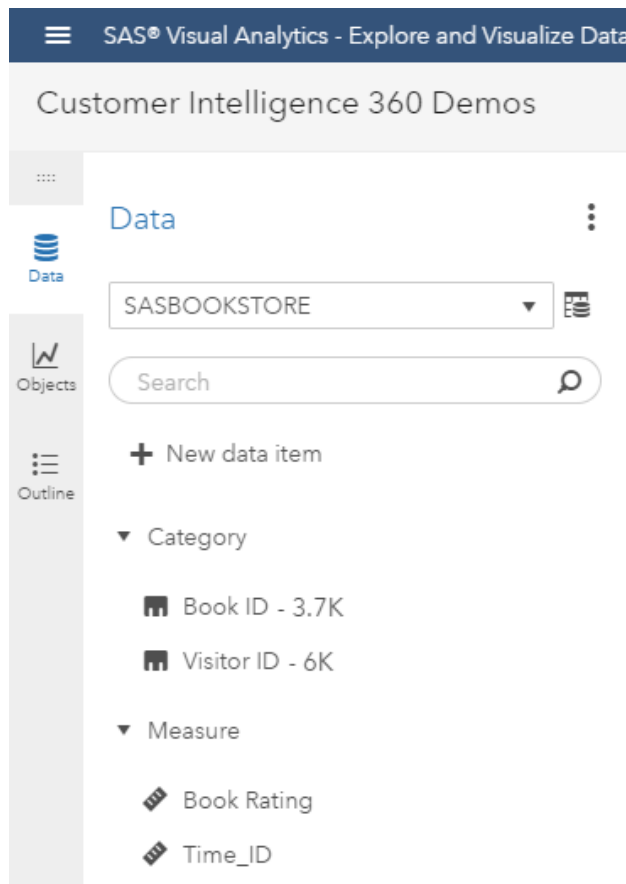
**Figure 6. Input Vector for Recommender Systems**

The factorization machine model is then equivalent to the following equation for predicting new ratings:

$$\hat{y}(x) = \hat{y}(u, i) = w_0 + w_u + w_i + \sum_{f=1}^k v_{uf} v_{if}$$

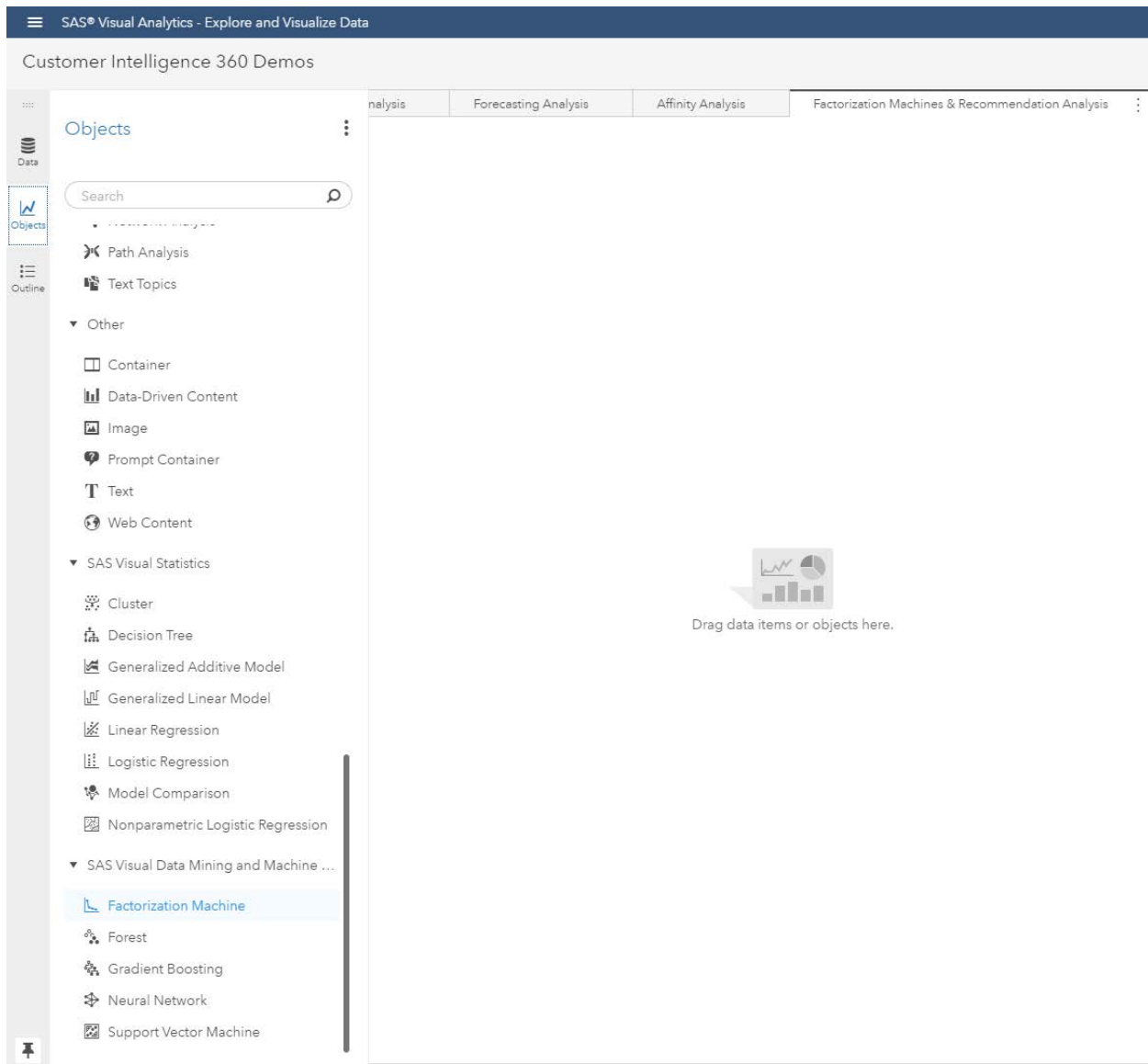
**Figure 7. Factorization Machine Equation**

Moving on, because this example draws on data based on visitor interactions with the SAS bookstore, the marketing strategy is to proactively offer recommendations of books users **didn't click on** explicitly but might like. Our analysis data set in support of this objective has four columns captured and provided from SAS Customer Intelligence 360: Book ID, Visitor ID, Book Rating, and Time ID.



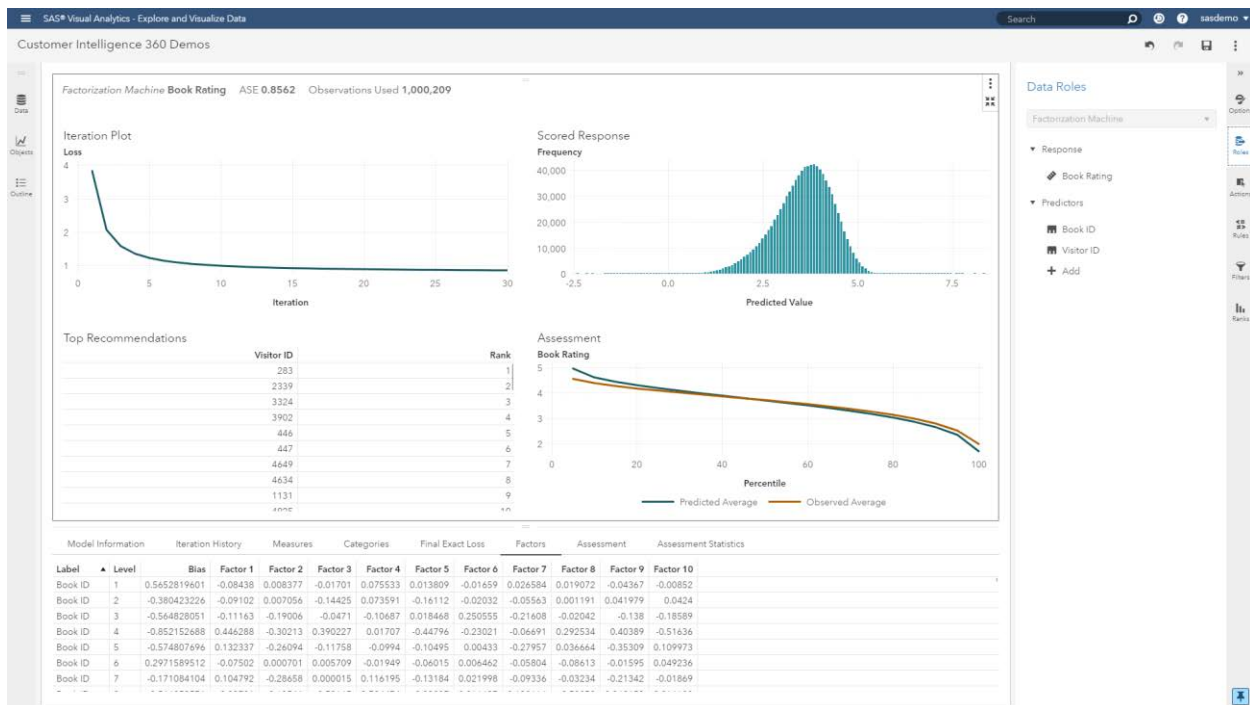
**Figure 8. Input Data Set Attributes**

Let's produce rating predictions for every specified Visitor ID and Book ID. Users select the factorization machine analysis object, drop it into the work space (see figure below), assign attributes to roles, and the model executes to provide results.



**Figure 9. SAS Visual Data Mining and Machine Learning - Factorization Machine Analysis Object**

Using the [FACTMAC](#)<sup>12</sup> procedure, you can call the action to implement the factorization machine model. It can be used to read and write data in distributed form to perform factorization in parallel by making full use of multi-core computers or distributed computing environments.

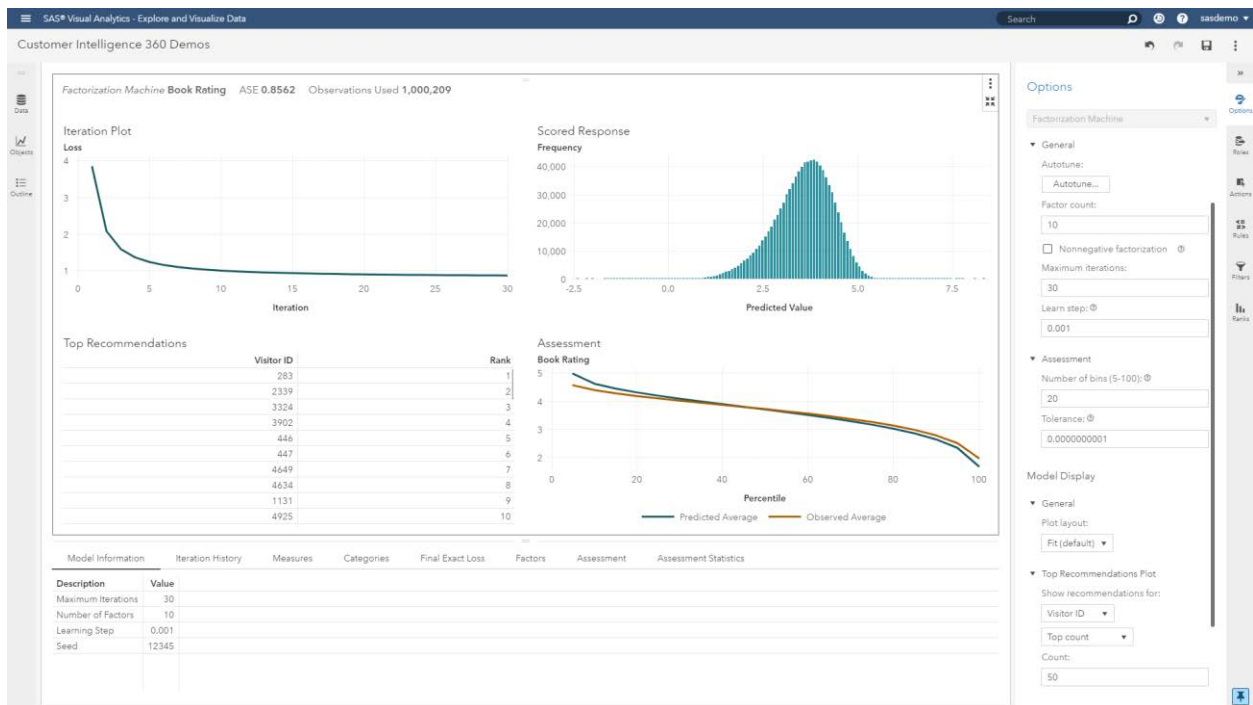


**Figure 10. SAS Visual Data Mining and Machine Learning - Factorization Machine Analysis**

Here is an introductory [video](#)<sup>13</sup> of building factorization machine visual models in SAS. For those readers who prefer programmatic approaches, view [this](#).

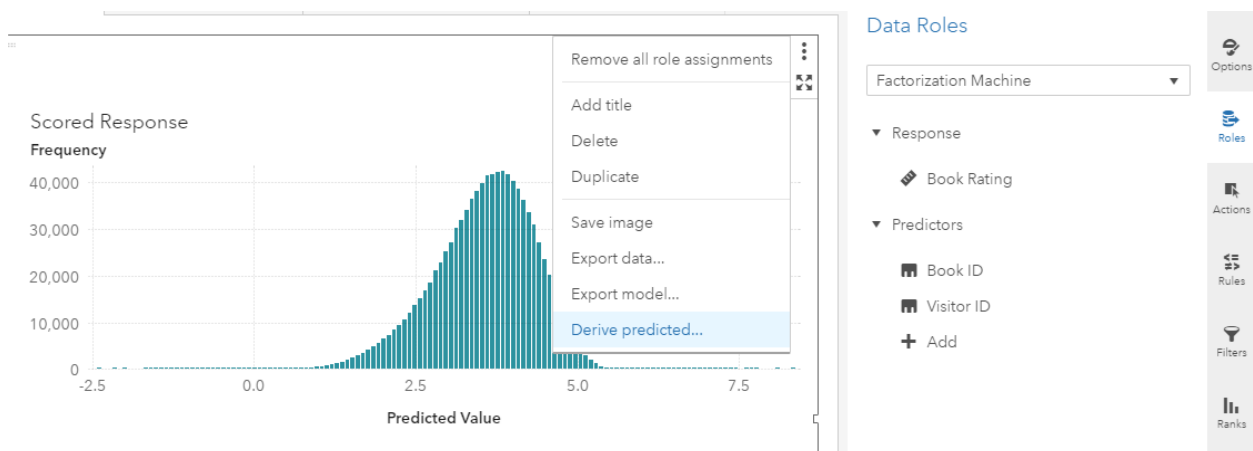
The FACTMAC procedure estimates factors for each of the predictors (Book ID and Visitor ID), in addition to estimating a global and a level bias. After specifying the target variable (Book Rating), the procedure computes the biases and factors by using the [stochastic gradient descent](#)<sup>14</sup> (SGD) algorithm, which minimizes the root mean square error (RMSE) criterion. In this method, each iteration attempts to reduce the RMSE. The SGD algorithm proceeds until the maximum number of iterations is reached, visually exemplified by the loss function within the iteration plot.

As shown in the image below, analysts have many optimization modeling options available. For example, the learn-step parameter controls how fast the stochastic gradient descent solver learns. Smaller values increase accuracy but might require a larger number of iterations to reach a good solution. [Auto tuning](#)<sup>15</sup> is supported in selecting optimal values for factor count, maximum iterations, and learn-step. Lastly, to ensure model stability, data partitioning for table stratification is available for training, validation, and testing.



**Figure 11. SAS Visual Data Mining and Machine Learning - Factorization Machine Modeling Options**

Further demystification of the model includes the scored response and assessment plots. The scored response visualization shows the distribution of the model's predicted book ratings. The assessment graphic shows the overall performance of the model by comparing the predicted and observed book ratings. Assuming we are happy with this model, the next step is to make the rating scores available for deployment.



**Figure 12. SAS Visual Data Mining and Machine Learning - Factorization Machine Model Scoring**

The output of this selection enables an analyst to produce the following data view.

The screenshot shows the SAS Visual Analytics interface with a table titled 'Customer Intelligence 360 Demos'. The table has three columns: 'Visitor ID', 'Book ID', and 'Predicted: Book Rating'. The 'Visitor ID' column contains the value 6039 for all rows. The 'Book ID' column lists various book identifiers, and the 'Predicted: Book Rating' column shows the corresponding predicted rating for each book. The interface includes a search bar at the top, a sidebar with navigation options (Data, Objects, Outline), and a right-hand sidebar with tool options (Options, Roles, Actions, Rules, Filters, Ranks).

Visitor ID	Book ID	Predicted: Book Rating
6039	2671	3.96701117
6039	3133	4.07701407
6039	942	4.47109115
6039	1014	4.15147538
6039	906	4.4566281
6039	915	4.12246352
6039	1269	4.46218305
6039	2300	4.43031883
6039	3037	4.39207049
6039	1081	3.93502783
6039	3549	4.09482994
6039	1934	4.07223195
6039	1212	4.85868789
6039	924	4.43070618
6039	1964	4.11357719
6039	1304	4.53262307
6039	1680	4.08834444
6039	1276	4.57233276
6039	3421	4.38797474
6039	930	4.52851192
6039	1223	4.74694425
6039	950	4.59334067

**Figure 13. SAS Visual Data Mining and Machine Learning - Factorization Machine Deployment Output**

Each user now has a predicted rating score for every product available in the SAS bookstore. And every visitor can have a rank-ordered set of scores associated with their profile. Rest assured, there are different approaches in making analytically scored data available within (and outside) of the SAS platform beyond a table. Here are some options that analysts have in helping their marketing teams:

- Scoring identifiable and anonymous traffic.
- Publish models in batch by calling the model through [SAS code, Python code, or REST APIs](#)<sup>16</sup>.
- Publish models in real time by calling the model through REST APIs using [SAS® Micro Analytic Service](#)<sup>17</sup>.

Specific to the usage of recommendation systems within marketing, SAS Micro Analytic Service is a powerful mechanism. For example, it can be called as a web application with a REST interface by SAS and other client applications. Envision a scenario where a visitor clicks on your website or mobile app, meets an event definition, and a factorization machine model runs to provide a fresh recommendation score to personalize the next page or screen of that digital experience. The REST interface (known as the SAS micro analytic score service) provides easy integration with client applications and adds persistence and clustering for scalability and high availability.

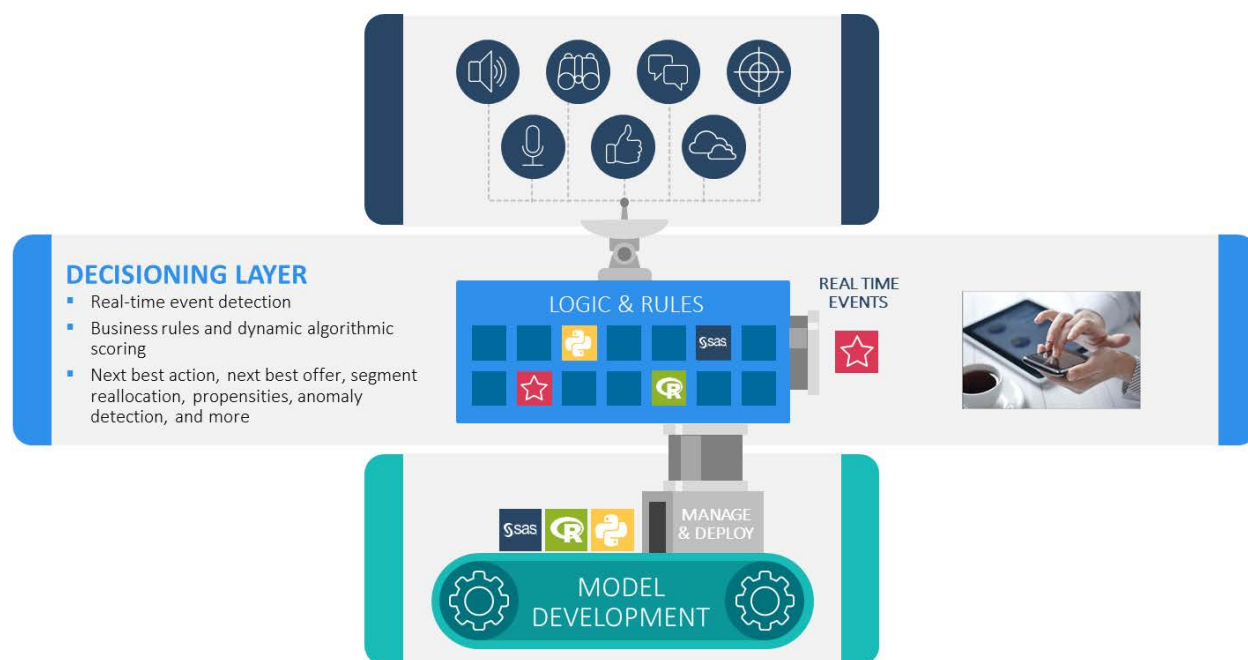
For more information about publishing and managing models in production, check out this [article](#)<sup>18</sup>.

## INTELLIGENT DECISIONING WITHIN SAS CUSTOMER INTELLIGENCE 360

A typical day brings countless business decisions that affect everything from profitability to customer experience. What is a reasonable price point? Which audience segments should I personalize offers for? When should I recommend specific content earlier in a customer journey?

**Daily decisions like these can alter the trajectory of a brand's business. And while one bad move might not seem detrimental, hundreds or thousands of such operational decisions can be. So, it's important that each decision is made with the best, most accurate information – while remaining consistent with organizational policy.**

The output of the factorization machine model leads to scoring that identifies the best offer (or book) to deliver within a consumer touchpoint. The decision can be made in real time for inbound interactions and triggered for outbound communications.



**Figure 14. SAS Customer Intelligence 360 - Decisioning Layer**

Let's walk through this. You have a prospect with a high recommendation score for a specific offer, that engages through social channels, but is under the age of 18. Your organization's policy is not to advertise to individuals below a specific age threshold, regardless of how high the analytical score is. The decisioning layer of SAS Customer Intelligence 360 allows you to combine analytical models, business rule sets, and conditional logic into customer treatments and publish the decisions for orchestration.

Rule sets capture the logic of business decisions by allowing users to codify the decision-making process used by your organization. The rules make the decision-making process

transparent and adaptable, enabling brands to respond quickly to new information about customers, segments, and markets.

Returning to our SAS bookstore use case, assume that I have been interacting with the **brand's owned digital properties across a visitor's** journey. After interacting with a call-to-action on a mobile app, I am redirected to a website and targeted with analytically recommended content.

The question is how did I configure event monitoring for that specific type of interaction with the mobile app? Within the user interface of SAS Customer Intelligence 360, there are a variety of interaction types that can be captured.

## 1 Select Event Type

Use events to identify how users interact with your content.

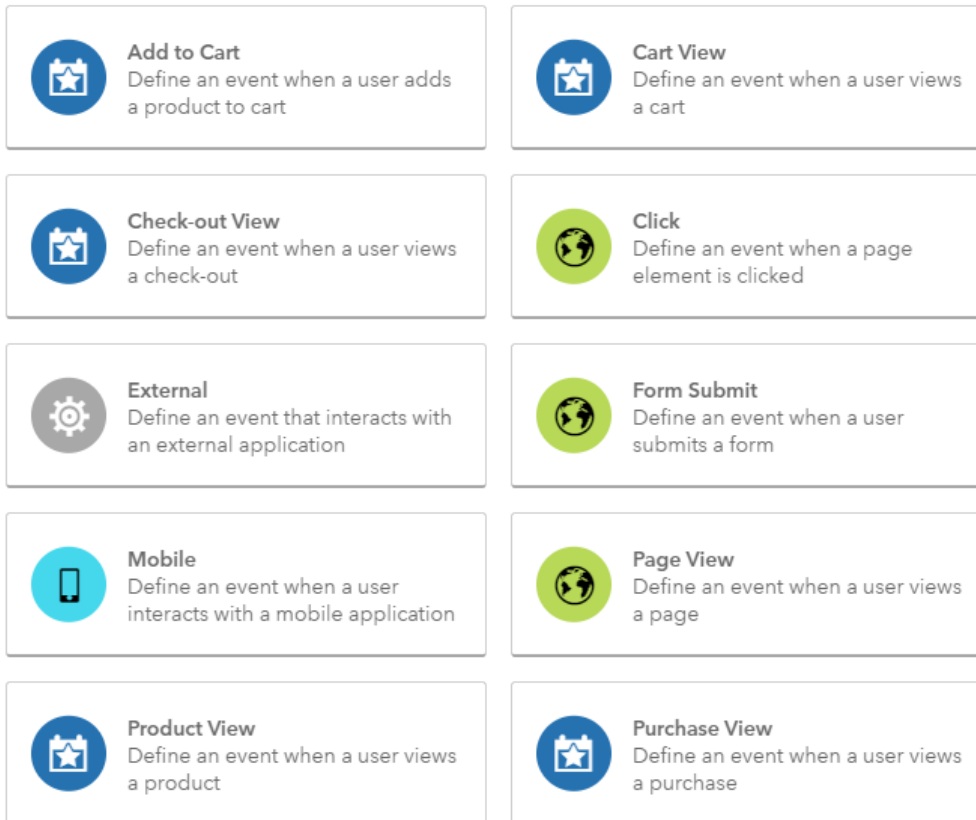


Figure 15. SAS Customer Intelligence 360 - Event Capture



For this example, we selected the mobile event type. After configuration is complete, it is that interaction on the mobile app that will generate an event in SAS Customer Intelligence 360 and trigger the targeting on the website.

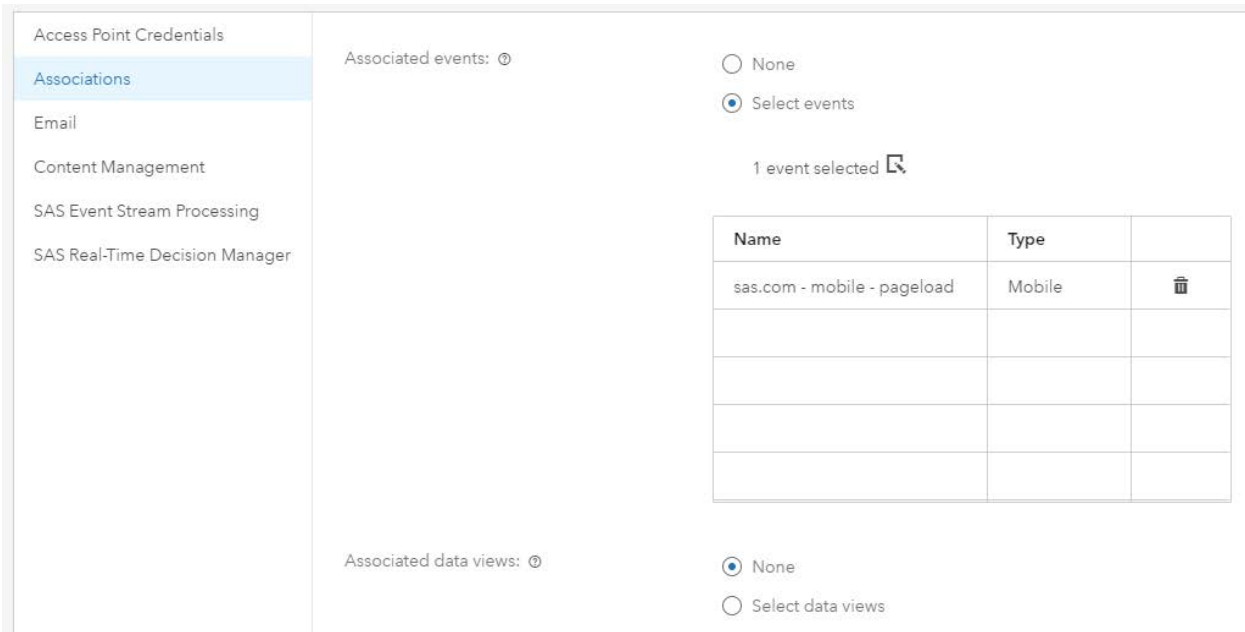
Now that we can observe every instance when that interaction occurs, we want SAS Customer Intelligence 360 to contact SAS Decision Manager on SAS Viya in real time for every visitor journey that meets the event definition. To do so, an agent is established to make the API connection.

The screenshot shows the configuration page for an agent in SAS Customer Intelligence 360. On the left is a navigation menu with options: General (selected), Email, Associations, Content Management, SAS Event Stream Processing, and SAS Real-Time Decision Manager. The main area is divided into several sections:

- Agent name:** DcM Agent
- Agent ID:** (empty field)
- Agent status:** Radio buttons for Active (selected) and Inactive.
- Agent credentials:** Includes fields for Access key, Last modified (Oct 25, 2018, 8:05:10 AM), and Tenant ID (ccf25c64ea00013af667e3f9). There are Replace and Remove buttons for the client secret.
- Associated IDs:** (empty field)
- Available items (3):** A list containing Customer ID, Email, and Login.
- Selected items (1):** A list containing Subject.

**Figure 16. SAS Customer Intelligence 360 - Authoring Agent Credentials**

Once the credentials are set, the association of the visitor interactions with the mobile app event and SAS Decision Manager can be defined.



**Figure 17. SAS Customer Intelligence 360 - Agent Associations with Events**

The value of unifying these two technologies within the SAS platform creates the following powerful benefits:

- SAS Customer Intelligence 360 can be used to stream real-time behavioral events to SAS Decision Manager.
- Real-time events from digital touchpoints can trigger decisions in SAS Decision Manager. These decisions can be used with other data sources such as CRM, demographics, transaction history, third-party data, and so on.
- Decisions executed by SAS Decision Manager can manage and execute analytic models, business rules, and conditional logic to return a recommended course of action.

**Let's break this down, one step at a time. When the mobile app event occurs, SAS Decision Manager will use the SAS Micro Analytic Service to perform the following:**

1. Query the latest CRM (customer relationship management) values for this specific customer regarding their education, income, and age from a database that SAS Viya is connected to on-premises or in the cloud.
2. Immediately apply a business rule that offer personalization cannot be targeted at individuals aged under 18.

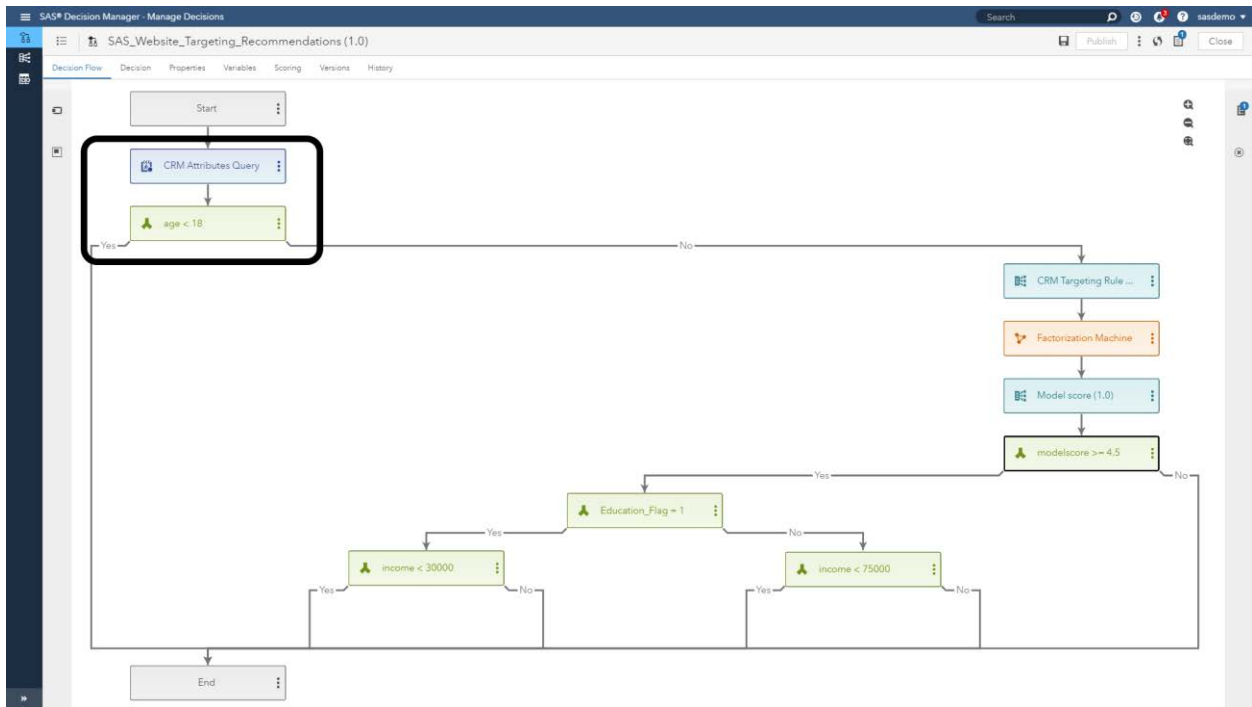


Figure 18. SAS Customer Intelligence 360 - CRM Database Query and Age Suppression

3. Run an auto-tuned, factorization machine model to produce a fresh recommendation score using digital experiential data captured and analytically prepared by SAS Customer Intelligence 360.

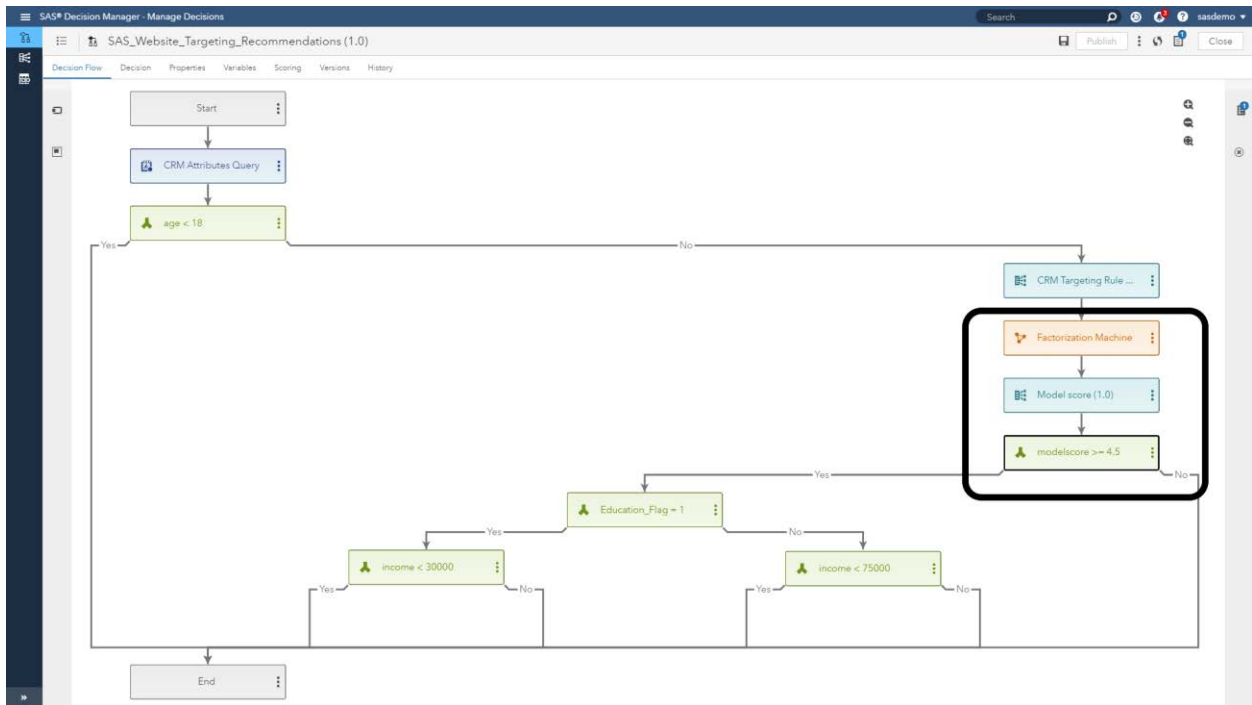


Figure 19. SAS Customer Intelligence 360 - Real-time Machine Learning Model Execution

4. Apply conditional logic using different combinations of additional CRM business rules.

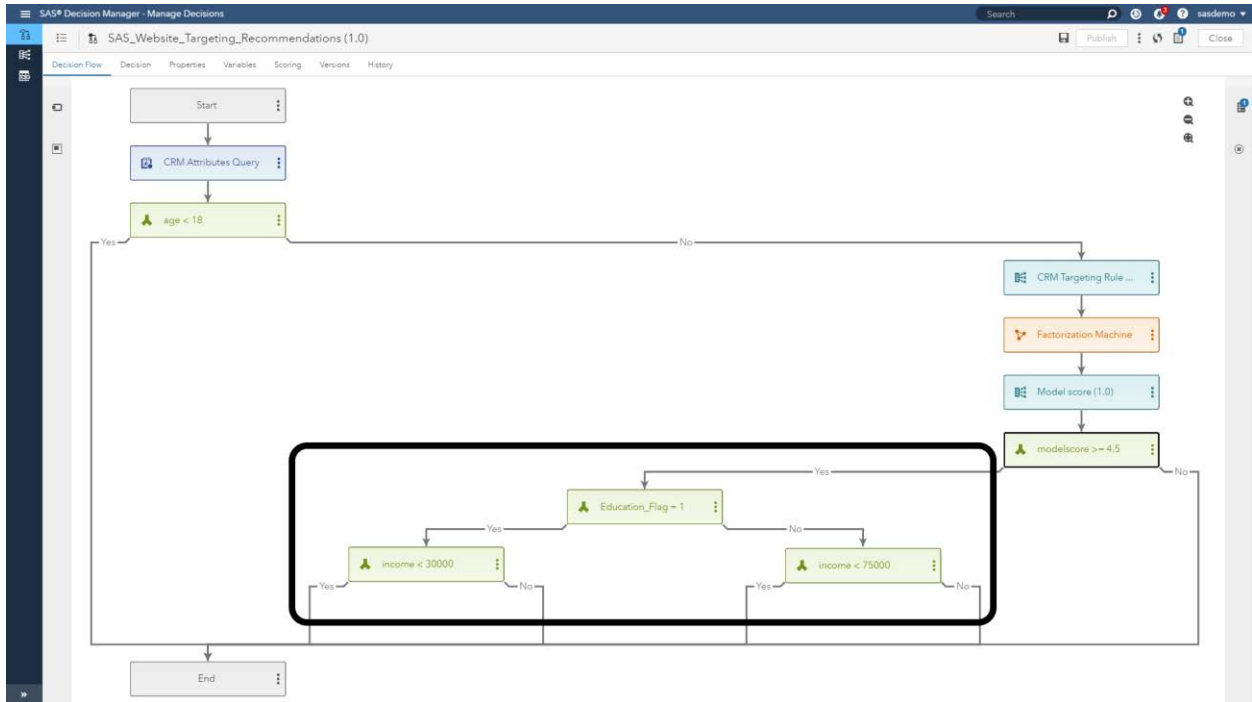


Figure 20. SAS Customer Intelligence 360 - Conditional Logic for Defining Segments

5. Based on the customer's assignment, produce four actionable segments with additional context beyond just an analytical score, and inform SAS Customer Intelligence 360 how to personalize the offer on the next page of the current web visit.

The SAS Micro Analytic Service is part of SAS Decision Manager. It is a powerful feature designed to execute analytical models and business rules against the latest data from online channels, combined with data from operational databases and other data sources. This entire process executes in milliseconds and works with SAS Customer Intelligence 360 to increase personalization precision without disrupting the customer's digital experience.

Whether the intent is to display a single recommendation like the following:

The screenshot shows the SAS Books website with a navigation bar at the top containing 'Products & Solutions', 'Books', and 'Phone: 1-800-727-0025'. A search bar is also present. The main banner features the text 'SAS® Books' and 'Free shipping to U.S. addresses. Download e-books directly from SAS - now available globally!'. Below this is a button to 'Subscribe to book news and special discounts'. The central focus is a 'Book of the Month! 40% off list price for one month only' promotion, with a book cover for 'Customer Segmentation and Clustering Using SAS Enterprise Miner' highlighted in a red box. At the bottom of the banner, it says 'Enter promo code BOM40% off list price. Discount expires July 31, 2018'. Social media icons for Facebook, Twitter, LinkedIn, and Google+ are on the right side.

Figure 21. SAS Customer Intelligence 360 - Single Product Item Targeting

Or if the intent is to allocate multiple recommendations at once like the following:










The screenshot displays the 'New Releases' section of the SAS website. It features six book covers arranged in a row, each with its title and author information listed below. The books are: 'JSL Companion: Applications of the JMP® Scripting Language, Second Edition' by Thomas L. Uhlig, George Z. Morgan, and Kevin G. Anderson; 'Data Management Solutions Using SAS® Hash Table Operations: A Business Intelligence Case Study' by Paul Dorfman and Don Henderson; 'Applied Econometrics with SAS®: Modeling Demand, Supply, and Risk' by Barry K. Goodwin, A. Ford Ramsey, and Jan Chvotik; 'SAS® for Forecasting Time Series, Third Edition' by John C. Brocklebank, David A. Dickey, and Boqiang S. Chao; 'Infographics Powered by SAS®: Data Visualization Techniques for Business Reporting' by Travis Murphy; and 'Mastering the SAS® DS2 Procedure: Advanced Data-Wrangling Techniques, Second Edition' by Mark Jordan. At the bottom of the section is a button that says 'View upcoming titles' with a right-pointing arrow.

Figure 22. SAS Customer Intelligence 360 - Multi-product Item Targeting

The beauty is all the execution ideas are options for the marketer to consider. When it comes to targeting audiences for web personalization, mobile cross-sell opportunities, or email acquisition programs, this decisioning output is crucial in including (or excluding) individuals for recommendations.

### 1 Select Task Type

Select the channel through which your content is delivered.

 <b>Direct Marketing</b> Create catalogs and various print marketing material.	 <b>Email</b> Prepare email content, subject, and address information.	 <b>In-App Message</b> Publish a context-sensitive message within a mobile application while the user is in the
 <b>Mobile Spot</b> Display a message on a specific spot within a mobile application.	 <b>Mobile Spot A/B Test</b> Compare different mobile content to see how it impacts conversions.	 <b>Push Notification</b> Display a mobile application push notification message on a mobile device.
 <b>Web</b> Display a message on a web site.	 <b>Web A/B Test</b> Compare different content to see how it impacts conversions.	 <b>Web Multivariate Test</b> Compare different combinations of content to see how it impacts conversions.

**Figure 23. SAS Customer Intelligence 360 - Multi-channel Delivery Capabilities**

The marketing strategy will lead with a recommendation concerning the best offer (or offers) to deliver within the touchpoint. The decision will select only the highest ranked proposition or propositions out of the possible book title offers, depending on the **individual's predicted score** or scores, their eligibility, and other relevant criteria. Here is an example of how a marketer would set up the nested targeting logic within SAS Customer Intelligence 360:

Name: \* Predictive Multi-channel Targeting

Description: Leverage analytical model scoring just as easily as traditional business rules for targeting and personalization.

All of the following

Predicted Book Rating	>=4.5
Age Group	Adult; Middle Aged
Education	Associate Deg; Bachelor Deg

Targeting Summary

**Predicted Book Rating : >=4.5**

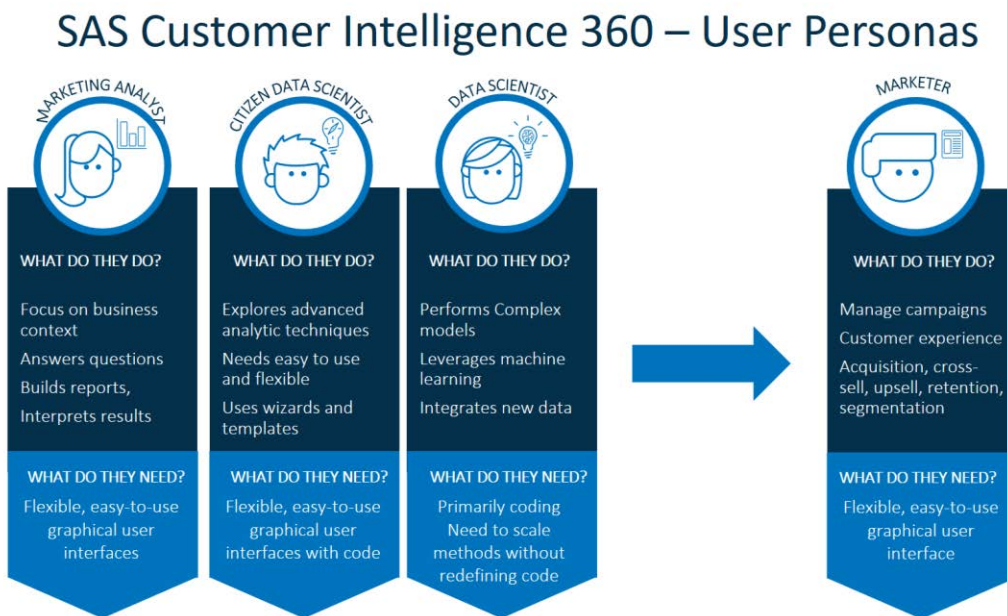
**AND Age Group : Adult; Middle Aged**

**AND Education : Associate Deg; Bachelor Deg**

**Figure 24. SAS Customer Intelligence 360 - Audience Targeting**

## CONCLUSION

SAS recognizes there are different user segments that leverage our platform, and this white paper focused on how analysts who prefer to build custom analytical recommendation models in support of the marketer's agenda for delivering customer personalization. Although not covered, for readers interested in automated recommendation systems embedded within SAS Customer Intelligence 360, read this [article](#)<sup>19</sup>.



**Figure 25. SAS Customer Intelligence 360 - User Personas**

At the heart of this white paper is the FACTMAC procedure, which enables you to solve a variety of tasks, from recommendations to predictive modeling, all of which involve sparse data. Thanks to a highly parallel optimization solver, PROC FACTMAC can handle very large data sets. This powerful and flexible method provides not only predictions but also meaningful factor representations that can give you insights into many types of business problems.

Although we took a tour of how SAS Customer Intelligence 360, SAS Visual Data Mining and Machine Learning, and SAS Decision Manager can work together, ultimately SAS wants to help marketers be effective through analytic techniques. Consumer preferences are difficult to predict. By exploiting the deep library of algorithms provided by SAS, intelligent decisioning features, and orchestration delivery, recommendations can automatically shape shift to meet the demands of the consumer and create brand relevancy through data-driven personalization.

## REFERENCES

1. Peppers, Don, Martha Rogers, and Bob Dorf. 1999. "Is Your Company Ready for One-to-One Marketing?" *Harvard Business Review*. Accessed March 1, 2019. <https://hbr.org/1999/01/is-your-company-ready-for-one-to-one-marketing>.
2. Grover, Suneel. "How Does a Marketer Know What to Test?" Available <https://blogs.sas.com/content/customeranalytics/2017/08/11/how-does-a-marketer-know-what-to-test/>. Last modified August 11, 2017. Accessed on February 28, 2019.
3. Grover, Suneel. "SAS Customer Intelligence 360: Goals, Propensity Models, and Machine Learning." Available <https://blogs.sas.com/content/customeranalytics/2018/05/30/sas-customer-intelligence-360-goals-propensity-models-and-machine-learning/>. Last modified May 30, 2018. Accessed on February 27, 2019.
4. "Micro-Moments." Google. Available <https://www.thinkwithgoogle.com/marketing-resources/micro-moments/>. Accessed on February 28, 2019.
5. Schaefer, Mark. 2014. "Content Shock: Why Content Marketing Is Not a Sustainable Strategy." Available <https://businessgrow.com/2014/01/06/content-shock/>. Accessed on February 26, 2019.
6. SAS Institute Inc. 2018. "Association Rule Mining Action Set." In *SAS Visual Data Mining and Machine Learning 8.3: Programming Guide*. Cary, NC: SAS Institute Inc. Available [https://go.documentation.sas.com/?docsetId=casactml&docsetTarget=casactml\\_rulemining\\_details01.htm&docsetVersion=8.3&locale=en](https://go.documentation.sas.com/?docsetId=casactml&docsetTarget=casactml_rulemining_details01.htm&docsetVersion=8.3&locale=en). (accessed February 24, 2019).
7. Silva, Jorge and Raymond E. Wright. 2017. "Factorization Machines: A New Tool for Sparse Data." *Proceedings of the SAS Global Forum 2017 Conference*. Cary, NC: SAS Institute Inc. Available <http://support.sas.com/resources/papers/proceedings17/SAS0388-2017.pdf>.
8. Rendle, S. 2012. "Factorization Machines with libFM." *ACM Transactions on Intelligent Systems and Technology* 3(3): 1-22. Available <https://www.csie.ntu.edu.tw/~b97053/paper/Factorization%20Machines%20with%20libFM.pdf>.
9. SAS Institute Inc. 2018. "Support Vector Data Description Action Set." In *SAS Visual Data Mining and Machine Learning 8.3: Programming Guide*. Cary, NC: SAS Institute Inc. Available [https://go.documentation.sas.com/?docsetId=casactml&docsetTarget=casactml\\_svdatadescription\\_details.htm&docsetVersion=8.3&locale=en](https://go.documentation.sas.com/?docsetId=casactml&docsetTarget=casactml_svdatadescription_details.htm&docsetVersion=8.3&locale=en). (accessed February 24, 2019).
10. SAS Institute Inc. 2018. "Recommender System Action Set: Details." In *SAS Visual Analytics Programming Guide*. Cary, NC: SAS Institute Inc. Available <https://go.documentation.sas.com/?cdcId=pgmsascdc&cdcVersion=9.4.3.4&docsetId=casapng&docsetTarget=n05bxq1zhsoxzun1padoh6m829y0.htm&locale=en>. (accessed February 25, 2019).
11. SAS Institute Inc. 2018. "Machine Learning. What It Is and Why It Matters." Accessed February 21, 2019. Available [https://www.sas.com/en\\_us/insights/analytics/machine-learning.html](https://www.sas.com/en_us/insights/analytics/machine-learning.html).
12. SAS Institute Inc. 2018. "The FACTMAC Procedure." In *SAS Visual Data Mining and Machine Learning 8.3: Procedures*. Cary, NC: SAS Institute Inc. Available [https://go.documentation.sas.com/?docsetId=casml&docsetTarget=casml\\_factmac\\_overview.htm&docsetVersion=8.3&locale=en](https://go.documentation.sas.com/?docsetId=casml&docsetTarget=casml_factmac_overview.htm&docsetVersion=8.3&locale=en). (accessed February 20, 2019).



13. SAS Institute Inc. 2018. "Building a Factorization Machine to Model Sparse Data in SAS Visual Data Mining and Machine Learning 8.1 on SAS Viya" [Video file]. Accessed February 19, 2019. Available <https://video.sas.com/detail/video/5360564238001/building-a-factorization-machine-to-model-sparse-data-in-sas-visual-data-mining-and-machine-learning-8.1-on-sas-viya?autoStart=true&q=factorization%20machine>.
14. SAS Institute Inc. 2018. "Stochastic Gradient Descent." In SAS® *Visual Data Mining and Machine Learning 8.3: Deep Learning Programming Guide*. Cary, NC: SAS Institute Inc. Available <https://go.documentation.sas.com/?docsetId=casdlpg&docsetTarget=p1i430hb7ri1fnn1511qu227wtbw.htm&docsetVersion=8.3&locale=en#n0dc5l3go7rgy7n119zwwwb30p1c>. (accessed February 18, 2019).
15. Koch, Patrick, Oleg Golovoidov, Steven Gardner, Brett Wujek, Joshua Griffin, and Yan Xu. 2018. "Autotune: A Derivative-free Optimization Framework for Hyperparameter Tuning" [Video file]. 24<sup>th</sup> ACM SIGKDD Conference on Knowledge Discovery and Data Mining. Available <https://www.youtube.com/watch?v=1g9d9b0-NJI>. Accessed February 27, 2019.
16. SAS Institute Inc. 2018. "Code Libraries and APIs for Building Apps with SAS." Accessed February 17, 2019. Available <https://developer.sas.com/home.html>.
17. SAS Institute Inc. 2018. "What Is SAS Micro Analytic Service?" In SAS® *Micro Analytic Service 5.2: Programming and Administration Guide*. Cary, NC: SAS Institute Inc. Available <https://go.documentation.sas.com/?docsetId=masag&docsetTarget=p1dhh0p6zuvf9cn1bxhcstz51ddq.htm&docsetVersion=5.2&locale=en>. (accessed February 16, 2019).
18. Grover, Suneel. "SAS Customer Intelligence 360: Model Management for Competitive Differentiation [Part 2]." Available <https://blogs.sas.com/content/customeranalytics/2018/11/30/sas-customer-intelligence-360-model-management-for-competitive-differentiation-part-2/>. Last modified November 30, 2018. Accessed on February 15, 2019.
19. Grover, Suneel. "SAS Customer Intelligence 360: The Digital Shapeshifter of Recommendation Systems [Part 2]." Available <https://blogs.sas.com/content/customeranalytics/2018/07/13/sas-customer-intelligence-360-the-digital-shapeshifter-of-recommendation-systems-part-2/>. Last modified July 13, 2018. Accessed on February 15, 2019.

## RECOMMENDED READING

Dean, Jared. 2018. "How to Build a Recommendation Engine Using SAS Viya." *Proceedings of the SAS Global Forum 2018 Conference*. Cary, NC: SAS Institute Inc. Available <https://support.sas.com/content/dam/SAS/support/en/sas-global-forum-proceedings/2018/2095-2018.pdf>.

## CONTACT INFORMATION

Your comments and questions are valued and encouraged. Contact the author at:

Suneel Grover, M.B.A., M.S.

Advisory Solutions Architect / Professorial Lecturer

SAS Institute, Inc. / The George Washington University, Washington D.C.

Email: [suneel.grover@sas.com](mailto:suneel.grover@sas.com)

LinkedIn: <https://www.linkedin.com/in/suneelgrover>

Twitter: @suneelgrover

Web: <https://blogs.sas.com/content/author/suneelgrover/>

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