Technical white paper

HP SPS Next Best Offer: how to re-think your marketing

Put your Customer at the center of your marketing

Table of contents

Despite all the hype to turn themselves into customer-centric companies, most Telco organizations are still product-oriented. Marketing departments, are still organized to sell products throught mass campaign and not to increase customer's expenditure promoting personalized services. But in the hype competitive telecommunication world, subscribers are inclined to spend more on the companies which offer personalized product and services. In order to increase their profit, Telecommunication companies must switch to a model where the customer' lifetime value is maximized; they have to embrace new solutions capable of recommending the right product at the right time in the right location: The Next Best Offer solutions.

The new marketing paradigm

Despite all the hype to turn themselves into in customer-centric companies, most Telco copanies are still product-oriented. Marketing plans always start from the definition of the product they want to promote. Only once the product is defined, marketing teams identify the broad market segments to target, set prices and promotions, and plan mass market campaigns. The interaction model is one-way: products are pushed into the selected segment throught mass market campaigns ("direct marketing"). But in the hype competitive telecommunication world, where customers are used to receiving personalized products and services, mass market campaigns are not longer effective. Customers are increasingly frustrated by generic offers they are bombarded by marketers; they would rather have relevant, personalized interactions and based on their's habits and preferences. Therefore users are more inclined to be loyal and to spend more to the companies which offer more personalized product and services. Research shown that customers are more receptive to offers made in the inbound channel. Industry analyst firm Gartner estimates a 10x improvement in sales with a real-time, customer initiated, relationship-driven conversation over traditional outbound channels, as shown in the following table:

Marketing type	Interaction type	Interaction way	Effectiveness	Example
Outbound	Direct marketing	From company to customer	1-5% response	Groupon
Inbound	Customer-trigger	Company interact with Customer on specifi events or situation	5-25% response	Facebook
Inbound	Customer-initiated	Company responds on customer's input	10-50% response	Amazon

Table 1 - Effectiveness of different interaction model

Telecommunication companies must shift from a model where product sales are maximized to a new one where customer's lifetime value is maximized. That means making products and brands subservient to long-term customer relationships and adopting solutions which enable one-to-one personalized marketing.

In customer-centric marketing:

- The sale goal is not to maximize product sales, but to maximize of the profitability per customer (ARPU).
- The interaction between company and customer is not longer unilateral, but becomes bi-directional. Feedbacks and behaviours analysis are fundamendal to understand customer's preferences. The interaction is moving from one-to-many to one-to-one.
- The main goal of collecting customer information is not longer meant to create targeted customer pools for new products, but to understand customer's behaviours and preferences and conseguentelly to promote personalized product and offers.
- Customer's loyalty plays a critical role, as account maintenance costs decrease in time and long term customers tend to be less inclined to switch, less price sensitive and are more likely to buy ancillary products.

In conclusion, marketing model is completely reversed: customer, first; then the product. Customers are engaged as individuals and not as a target group; products and services promotion is proactivelly based on customer's needs and preferences.

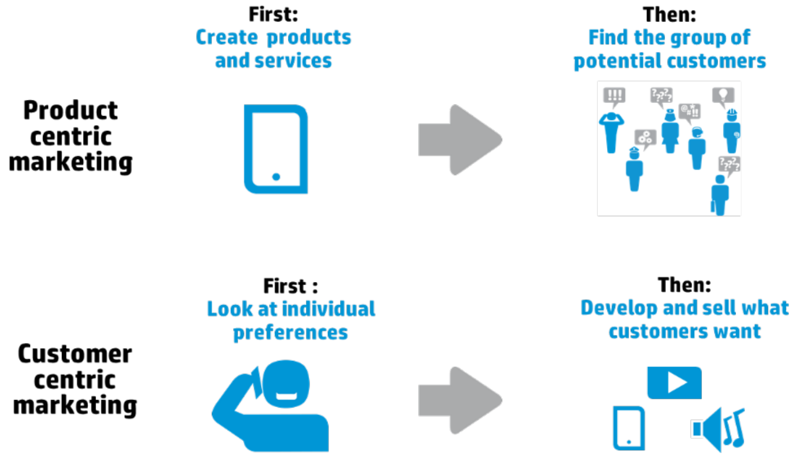


Figure 1 - New customer-centric marketing paradigm

Adopting this model will allow Telecommunication operators to create an awesome customer experience, which will lead to long-term satisfaction and loyalty to your customers.

Note
Inside Customer-centric marketing, outbound marketing will keep playing an important role within the overall customer experience; rather than being a direct sales channels, they should encourage customers to get engaged with the more effective inbound channels.

The Next Best Offer solution

Customer-centric marketing isn't really new model, in the past, shopkeepers and retail sales people were intimately familiar with their customers. They personally knew each client and its individual preferences, and they could always recommend the right product to buy. Even if this model is extremelly efficient in selling and creating customer loyalty, it has a big limit: it doesn't scale, it can't be applied in hyperstore and mass market era.

But now with the availability of low cost hardware and storage and of sophisticated analytics, Telecommunication operators - and almost any commercial company – can re-create customer-centric marketing and use it on large scale. They can create systems caable identifying each customer's preferences, purchase history, and purchasing context in order to recommend the right product or services that customers are most likely to be interested in purchasing; all this, at the right moment and at the right place. These system are known with the name of: Next Best Offer (NBO).

The picture below shows a typical example of a NBO systems:

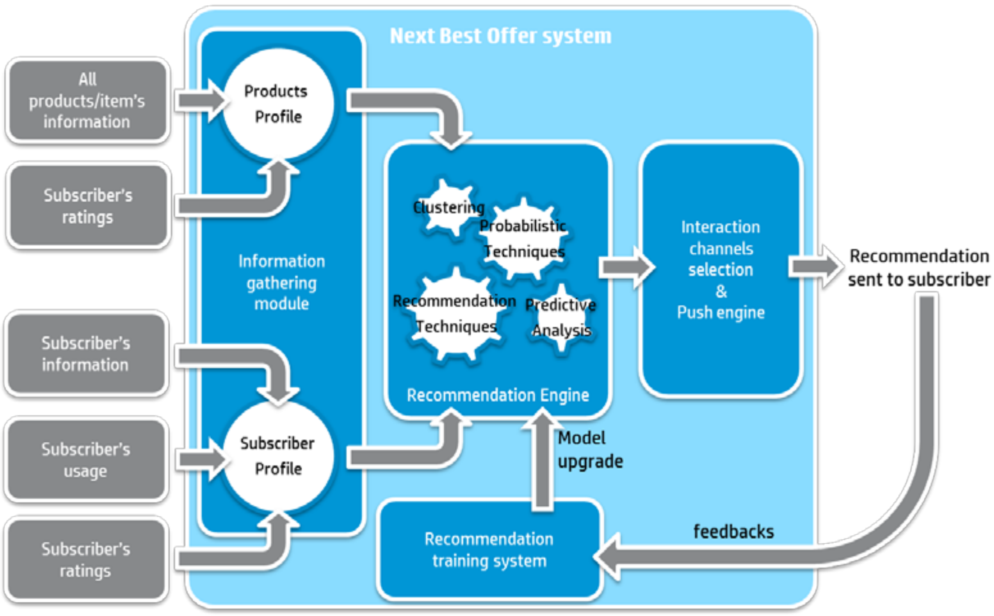


Figure 2 - Example of NBO logical architecture and data flows

A NBO solution is generally formed by the following logical modules:

Information gathering module

It is responsible for two main activities:

- Collecting raw data on Telco sellable items (products, services, contents or promotions) and Subscriber's information
- Organized, correlate, categorize this data into usable information for Recommendation Engine. In this stage, product's and subscriber's profiles are created. This information are stored in the NBO engine and continuously updated.

Important
A good practice would be to correlate these profile with as many internal or external sources as possible, in order to improve the quality and the richness of the information provided to the recommendation engine.

Recommendation engine

It is the core of any NBO system. When sa pecific event occurs – f.e. the subscriber is in a specific area or he is surfing on a particular website or Telco is launching a new services or other – the recommendation engine – previously loaded with a decision model - "matches" subscriber's profile with the Telco items to find any possible association. The item with the highest "matching" score is sent as recommendation using the user's preferred interaction channel.

Important
Recommendation Engines are a subclass of information filtering systems which try to predict the rating or preference that a user would give to an item or social element he had not yet considered. Recommedantion engines use a model built from the characteristics of the item or the user's social environment.

A good recommendation is something having a high probability of acceptance by the user.

Interaction channel selection module

It is in charge to select:

- the best channel to push the recommendation to the subscriber – f.e. call, SMS or push message –
- the best time – f.e. late afternoon at home or early moring - to interact with the customer.

Recommendation training or Evaluation module

Customers can buy the promoted item using a self-care portal or selecting a link or thorug other interaction mechanism. Whens the subscriber makes their choise, their feedbacks (positive or negative) is collected by the system and sent back to the Recommendation training or Evaluation module to refine and update the decision model inside the recommendation engine.

Important
The recommendation training module works on a subset of production data called a *training data*. The training data isn't a complete copy of production data, but rather just subset of data to provide a representative sample of your customers and your products.

Reporting or Visualization System

It is used to evaluate the efficiency of the recommendation model and to refine it.

Recommandation Engine

Recommendation engines are the heart of any NBO solution. In today's content-rich world, consumers are overwhelmed by the choice of products available, and this create an enormous frustration, as the time they have to spend searching for what they want/like if often longer than the time to "consume" the content.

Recommendation engines are the answer to this problem: they reduce information overload by estimating relevance of an item, product of service for a specific user. They also identify product alternatives, and suggesting other services that were also purchased by other customers. Recommendation engines help both marketing and final users to identify the services or the product that matches customer preferences: they recommend the right service to the right people at the right time.

As can be easily imagine, the key entities in any recommendation systems are the *users* and the *items* (f.e. a product or a service or an offer). Users have preferences for certain items and the aim of recommendation systems is to determine the user's degree of preference for that item.

Recommender systems can be seen as a function[1] which provide the relevance score of an item for a specific user.

Relevance Score = F (item features; user preference)

The input parameters of this functions are user's ratings and preferences and item's metadata, while the output is an item list ordered by relevance for the target user.

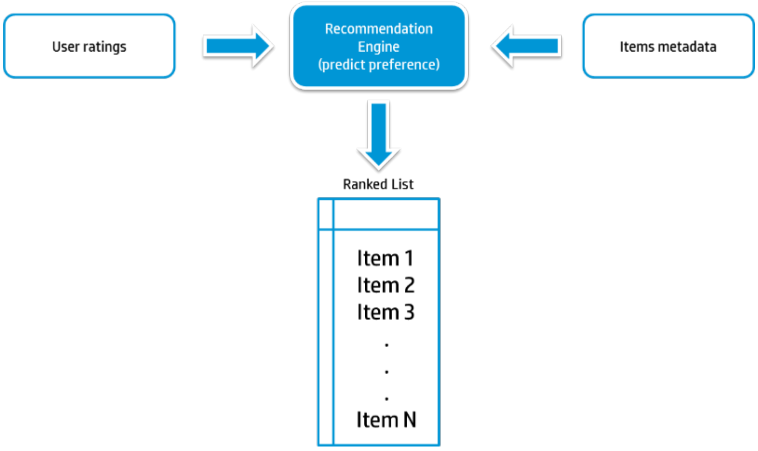


Figure 1 - Logical architecture of recommendation engine

Recommender systems algorithms are generally based on the two following paradigms[2]:

- Collaborative recommendations - where the recommendation is based on the similarity of the user ratings for two or more items
- Content-based recommendation – where the recommendation is based on the similarity among items.

To improve efficiency in the recommendation, these techniques are often combined in a mix model called: Hybrid Recommendation model.

Collaborative Recommendation

These recommendation algorithms are based on product purchasing behaviours of the target subscriber as well as those of other subscribers. They work by finding similar customers in the database: look for a set of customers who have bought or rated the same items and then recommend the rest – f.e. you belong to a community who likes product Y, then then system proposes product Y to you too.

[1] Recommendation systems are a subclass of information filtering system that seek to predict the 'rating' or 'preference' that user would give to an item (from Wikipedia).

[2] There are other recommendation paradigms, f.e.:

- Personalized recommendations: bases on user profile and contextual parameters – f.e. if subscriber X likes running and he is near sport shop, then send him a promotion for running shoes.
- Knowledge-based recommendation: based on user explicitly defined set of recommendation rules - f.e. suggest me a product based on the information I provided to you.

Important
These techniques are based on the assumptions that users give ratings to catalog items (implicitly or explicitly) and user preferences remain stable and consistent over time.

- Esplicit rating - The item's ratings are provided by the users for products used. F.e. User provides a rating (scale 1-5) of the product he bought or User selects "likes" on product's facebook page.

  The main problem of this rating is that users are not always willing to rate many items, so the number of available ratings tend be small, impacting the quality of the recommendation.

- Impliciti rating - The item's ratings are estimated from subscriber's behaviour. F.e. if a user buy a product, this item is score 1 (Unary rating) or if a user opted for a product several times, then his preference for the product is rated on a scale 1-5 (real rating).

  The main limits of this rating is that user's behavior may not be correctly interpreted

There are two main type of collaborative recommendations:

1. User-based collaborative recommendation – Use the similarity between user behaviour to make predictions. F.e. given an target user X and an item *i* not yet seen by X
   a) Find a set of users (peers/nearest neighbors) who liked the same items as X (similarity) in the past and who rated item *i*. This step is generally done using a similarity technique, f.e. Pearson correlation or Cosine similarity or even clustering technique
   b) Use a predition model (f.e. the average of their ratings) to predict if X will like item *i*. This step is generally done using average measures.

   To improve these metrics/predictions some correction factors are use to weigh both the neighborhood's selection and the item's features.

2. Item based collaborative recommendation - Use the similarity between items to make predictions. F.e. given an item P which has been positively rated by user X, I will recommend to X all items (or the Top N items) which have similar rating of P.
   a) Item's ratings are seen as vector in n-dimensional space
   b) Item's similarity is calculated based on the angle between the vectors

   All item-based algorithms[3] use corrections mechanism to improve the precision of the similarity analysis and to reduce the computation capability needed.

Content-Based Recommendation

These recommendation algorithms are based on product features similarities and a profile of the user's preference. They utilize a series of discrete characteristics of an item in order to recommend additional items with similar properties – f.e. if a like a book from author Z, then propose me other books from the same author. In other words, these algorithms try to recommend items that have similar features to those that a user liked in the past.

Content-based systems are based on the creation of:

- Item profile – it is a record or a set of records representing the item's features. F.e. in a case of a movie, item's features should be: actors, directors, genre, production date, movie company … To create an item's profile, analytic algorithms are used, caable to extract structure and unstructured information by the items

- User profile – it a record or a set of records with the same components of the item's profile and which describe the user's preference. F.e. each user profile will contain information on the genre, actors, movie … liked by the user.

[3] Example of collaborative algorithms are:
- User Based
- Item-Based
- Similarity Fusion
- Personality Diagnosis
- Regression Based
- Slope One
- Latent Semantic Indexing
- Cluster Based Smoothing
- Item Mean
- Simple Mean Based
- Tendencies Based

The user's preferences are often weighed to highlight the importance of a feature with respects others for this user.

These two profiles can be represented as two vectors, and the combination of these vectors is a Users-Items matrix which is used to recommend items to user based on item's content.

This recommendation approach depends on how information is retrieval (to create a rich as possible item's profile), on how information is filtered (to reduce not relevant features/information) and on how information is organized (to classify a feature always in the same way – f.e. a specific song is always classified as "rock" and not as "alternative rock", "pop rock", "heavy metal" ...)

Important
Content-based techniques are similar to the item-based collaborative recommendation, but in this case the similarity is not calculated on the item's rating, but on items' attributes (f.e. genre, author, editor, creation date ...).

Hybrid Recommendation

Content-based ad collaborative methods have their advantages and also have certain disadvantages, some of which can be solved by combining both techniques to improve the quality of the recommendation. Indeed, combining multiple techniques often help to augment the strength of each constituent technique, while minimizing their drawback. The systems which combine both methods are called Hybrid models.

	Collaborative	**Content Based**
Advantages	• Simple, quick online processing • Product meta-data is not required	• Simple, quick online processing • It can easly handle recommendation of new products • It usually performs better than item based when data are sparse
Disavantages	• Not good for new products recommendation • Can't handle sparse data (data where subscriber ratings are not available)	• Product meta-data is required • Recommendation techniques is not cognizant of the quality of the products (no way of finding out whether the product is good or bad)

Table 1 - Advantages and disavantages of collaborative vs. content based recommendation

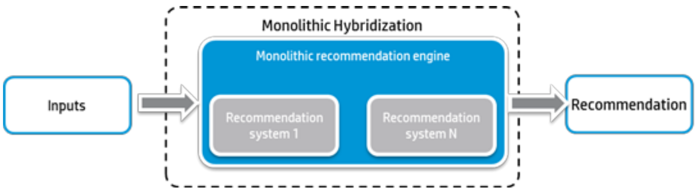
Hybrid models are based on the combination of the multiple analytical and recommendation techniques that can be implemented in several ways: by making content-based and collaborative-based predictions separately and then combining them; by adding content-based capabilities to a collaborative-based approach (and vice versa); or by unifying the approaches into one model. These combinations are called hybridization designs.

There are three main different hybridization designs:

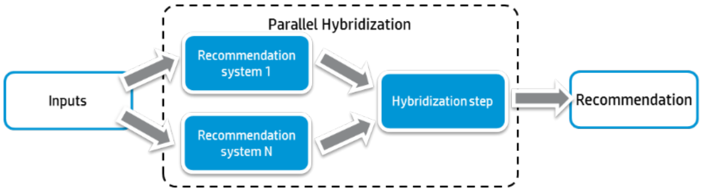
- Monolithic design
- Parallel design
- Pipeline design

Monolithic design

In this design there is a single monolithic recommendation component, which combine different features (f.e. Content-boosted collaborative filtering) and knowledge sources (f.e. ratings and user demographics or explicit requirements) of different paradigms.



Parallel design
In this model several recommendation systems are used in parallel on the same input, the output recommendations are combined and weighed by a hybridization element.



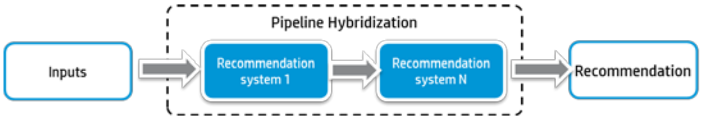
An example of parallel design is provided by the combination of Content based and Collaborative recommendation techniques. User's product ratings are used as input to a Collaborative recommendation engine producing content-filtering (CF) product preference scores. In parallel user's product ratings and product's features are used as input to a Content-based recommendation engine producing content-based (CB) product preference scores. Both product preference scores (CF and CB) are provided to a weighed average of preference score engine who produce the final preference list.

The combination of Content based and Collaborative recommendation model allows to overcome some of the main drawbacks of the two classes of recommenders as shown in the table below.

Technique	**Drawbacks**	**Solution**
Collaborative Recommendation	Inefficent to recommend new products without or with limited ratings	The use of content-based allows to rate products without or with limited ratings
Content-based Recommendation	Product quality (*taste*) is not considered by the recommender	Collaborative recommender using product ratings can produce recommendation based on the product quality

Table 2 – Example of hydrid model recommendation drawbacks mitigation

Pipeline design
In this model several recommendation systems are used in pipeline. One recommender system pre-processes some input producing a recommendation list. This list is used as input for the subsequent one which refine it in cascade: successor's recommendations are restricted by predecessor and subsequent recommender can't not introduce additional items. The recommendation list is continusly reduced.



An example of pipeline design is provided by another combination of recommendation techniques: Cluster analysis and Collaborative recommendation engines. Clustering techniques are used to group users by similarity using their demographic information (age, gender, home, city, profession, etc ...) and, if need be, their preferences (genre, movies, singer, music, directors ...). After that, user-based collaborative filters are used to predict the item to be recommended.

The usage of clustering techniques to group subscribers allows the system to run similarity calculations on smaller and more homogeneous group of neighbors producing more precise recommendations.

HP Next Bext Offer solution

The HP Next Best Offer solution is built on top of HP Smart Profile Server platform (HP SPS).

HP Smart Profile Server (SPS) analytic platform is a new generation of analytic systems enabling both deterministic and associative/predictive/recommendation models/techniques to derive insights that can be used improve customer sadisfation and loyalty. It identifies your customer preferences and needs:

- Score your customers activities
- Identify best matching services based on customer behaviors
- Recommend a list of ranked best matching services

HP SPS analytic platform consisting of the following logical modules:

- Data Management module
- Analytic Layer
  - Analytics module
  - Real Time Decision engine
  - Data orchestration and workflow
- Visualization layer

HP SPS runs on HP HAVEn big data architecture which provide the software technology infrastructure for managing in real time big data and fast analytics.

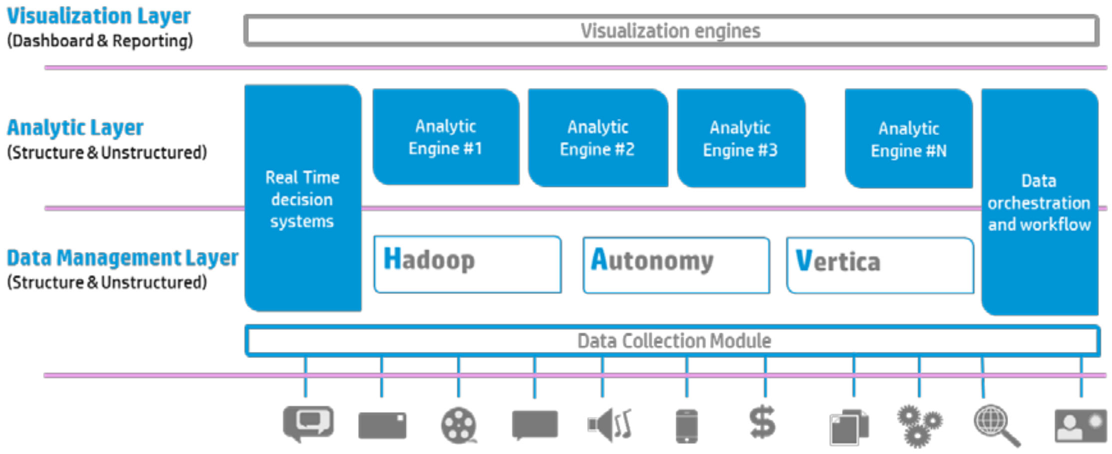


Figure 3 - HP SPS logical architecture

Data Management module

The HP NBO Data Management (DM) module is responsible to collect, enrich, correlate and prepare both subscriber's and product's information for the recommendatione engines.

As seen in the previous chapter the hybridation of collaborative and content-based methodologies produces more efficient recommendation systems, the Data Management module plays a key role in the whole solution, as it is in charge to collect as much data as possible to create the richest possible customer's and product's profiles. For this purpose, the HP DM has been designed to collect and correlate any data from inside and outside the company

The Data Management module collects data from the following sources:

- Subscriber's content based analysis
  - CRM (f.e. subscriber demographic data, Billing data, personal information, Trouble Tickets …)
  - Enterprise DWH (f.e. subscriber segmentation …)
  - Network (f.e. traffic patterns, application usage, web surfing, content used, media watched, KPIs …)
  - Location-based services (f.e. real time indoor and outdoor position using WiFi, GPS data, …)
  - Social media data (f.e. facebook …)
- Item's content based analysis
  - Implicit rating on contents (f.e. content consumption, used products, watched and listened media, purchased services and products …)
  - Esplicit rating on content and product
  - Other espliciti rating (f.e. user preferences on how and when he wants to be contacted back …)
  - Content Categorization DBs

From the architectural point of view, the HP Data Management Module is organized in :

- The data collection layer composed by:
  - Mediation and ETL platform such HP eIUM to gather and correlate data from Network and IT systems
  - Social media collector such HP IDOL to collect information from social media and/or from unstructured sources
- The Data archive and analytics platforms:

- Hadoop to store the raw data
- HP Vertica as analytic NoSQL database to run the analytics procedures
-

Subscriber profile
Even if generally speaking, item-based collaborative filtering is better than user-based one at precision and computation complexity, in the case of Telecommunication Operators, user's profile and user-based recommedantions play an important role as Tleco operator can collect a lot of information around their subscriber, so their user profile can be extremelly rich and they will allow to increase the level of efficency of the recommedations. For this reason, the HP NBO solution works on both item-based and user-based models, and it creates extremelly rich subscriber's profile correlating all information available inside and outside Telco companies.

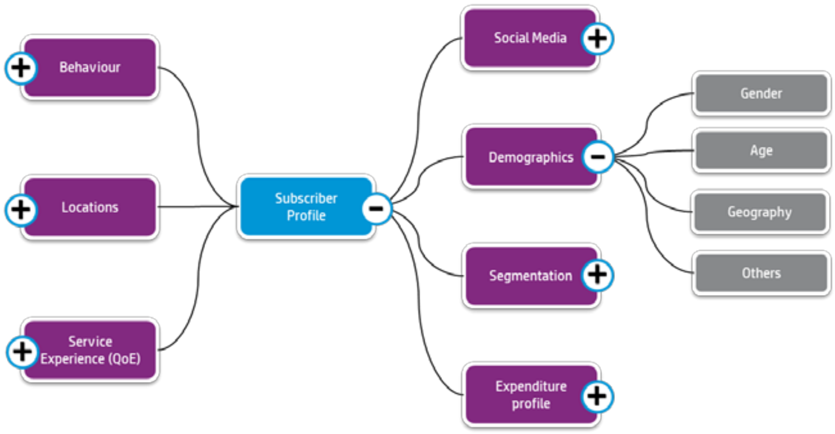


Figure 4 - Example of the components of subscriber profile

Analytics Layer

The analytic layer is the core of HP NBO solution and it contains the analytics engines and models for recommendations.

As recommendation models based on the combination of information filtering techniques (hybrid models) are more efficency of the ones based of a single techniques, the HP NBO solution recommendation engine is based on the combination of different analytics procedures which produce very high prediction quality and solve the cold start problem.

Important
The cold start problem happen when the system needs to recommend an item which hasn't been rated.

The recommendation model used inside HP NBO solution is based on a steped approach involving the following techniques:

- Items and User clustering
- Hybrid collaborative model
- Recommendation training and feedback module
- Orchestration
- Visualization Engine

Items and User clustering:
A mechanism used to improve the prediction quality and to solve the cold start problem, is to use the attribute of items in item-based collaborative models. The items are clustered by similarity using their attributes. The results of the clustering activity are used to create a new item-rating matrix richer than the traditional ones. The idea behind this model is quite simple: the item clusters, based on item's attributes, are used to expand the traditional item-rating matrix as shown in the table below:

	User 1	User 2	User X	Cluster 1	Cluster M
Item 1	....	....	....	....	....
Item 2	.....	....	....	....	....
Item N	.....	....	....	....	....
	Item rating matrix			Group rating matrix	

The clustering of items and users based on their attributes improves the correctness of collaborative similarities and mitigates the cold start problem – as it provides ratings also for the items that have never been rated – and it reduces the hardware resources's consumption while calculating recommendations - as the recommendation similarity is calculated on a subset of the whole matrix.

Similar prediction quality improvements are obtained using the same approach with the user attributes.

Hybrid pipeline collaborative model:
The new rating matrix obtained by the merge of item-rating and group rating matrix are used as input in the HP NBO pipelined recommedation model to calculate the similarity and make the predictions for the user. To improve the recommendation prediction quality and to mitigate the well known problem of the filtering information techniques, HP NBO engine is based on a pipeline of recommendation techiniques, when a techiniques can't provide a good recomemdation for a specific product to a user, it is hybridized with other techniques to improve the final prediction. The overall schema is shown in the following picture:

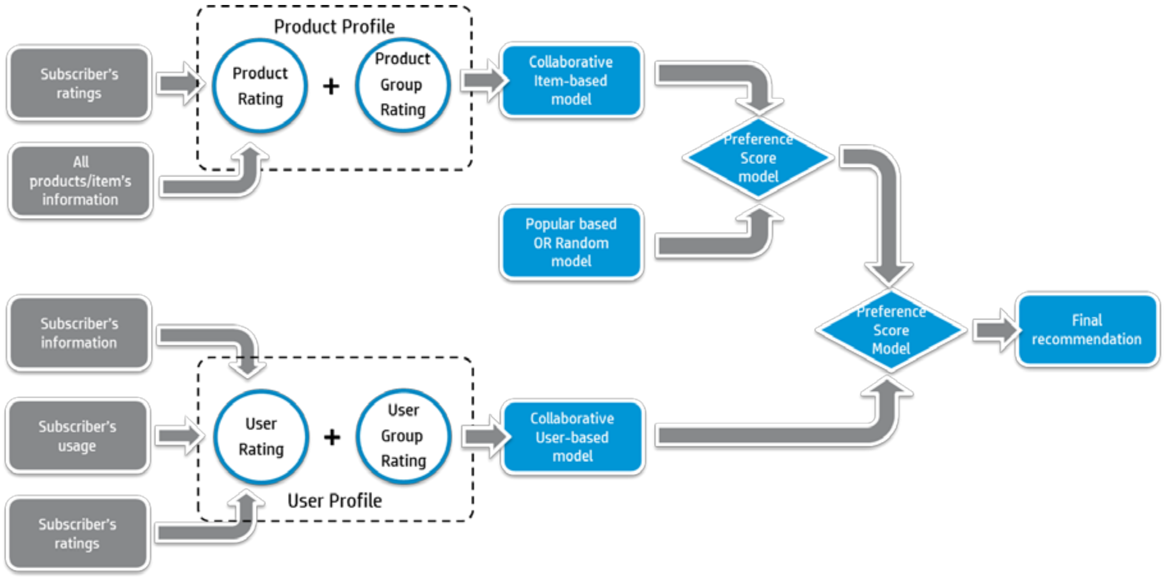


Figure 5 – Simplified view of HP NBO recommendation pipeline

Recommendation training and feedback module
The HP NBO recommendation training and feedback module is used to evaluate the optimal combination of paramters for recommendation engine by assessing how efficient the recommedations provided by the system are to help the user "consume" the products.

This module is used in two different stages:

1) Training Stage- At the beginning of HP NBO project to train the overall system using test data. In this stage, recommendation evaluation techniques are used to compare the predicted output of recommenders with the actual data (test set). Their outputs consists in predicted ratings, ranks and classification of items into Good/Bad. Three aspects are important:

- **Accuracy of each of predicted output attributes-ratings** – The technique used to compute the prediction is the *Mean Absolute Error (MAE).* It measures the average deviation between predicted recommendation scores and actual rating values in the test sets.
- **Accuracy of Classification** – it is based on the analysis of the following parameters

		Proposed by Recommender: Yes	Proposed by Recommender: No
Liked by User	Yes	Correct predictions	False Negatives
	No	False Positives	Correct Omissions

:

  - o **Precision:** Percentage of recommended items that were correct

    (*Correct Predictions*) / (*Correct Predictions + False Positives*)

  - o **Recall:** Percentage of relevant items that were recommended

    (*Correct Predictions*) / (*Correct Predictions + False Negatives)*

  - o **F1 metric:** Universally comparable measure

$$F1 = \frac{2 * P * R}{P + R}$$

- **Accuracy of Ranks** – It Is based on two rank accuracy indicators: *"Rankscore"* and *"lift index"*. They are calculated by taking into consideration the fact that accuracy of the initial ranks has the highest significance

2) **Feedback Stage**- During production time, this module is used to adapt the recommendation engine to the subscribers' changing preference and response pattern. The feedback loop evaluates the optimal combination of parameters for recommendation algorithms by assessing how efficient the recommendations are in helping customers consume the products.

   The efficiency of a recommendation technique is computed using cross validation with different combinations of parameters. The typical recommendation evaluation measures used are:

   - F-Score
   - Sensitivity
   - Specificity

   The results are visually presented in a dashboard to enable business analysts to choose the best combination based on the feedback data.

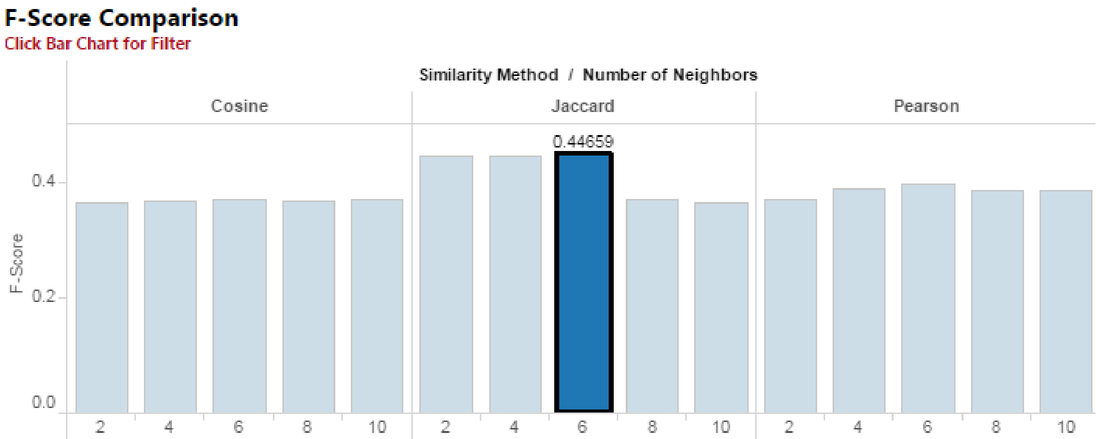


Figure 6 - Example of efficency analysis using F-Score evaluation score

Real Time decision engine

HP NBO Real Time Decision Sytems is a sub-module of Analytic Layer in charge to interact with Telco system to trigger the recommednation. It is based on CEP component which correlates the events together, and when a significant pattern occurs, it triggers a real-time decision interacting with business logic module.

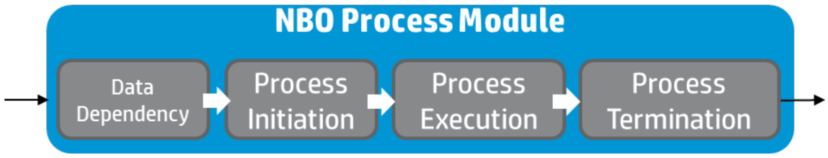
Orchestration

HP NBO recommendation engine is a quite complex process where single tasks and subprocesses are managed by a module called orchestrator. It is a flexible Business Process Management (BPM) module which allows to create, execute and monitor recommendation tasks, throughout whole recommendation process life cycle.

The key component of the HP NBO Orchestartion is the NBO-Process-Module, which is responsible for carrying out a single task. It includes two fundamental functions: scheduling and ad hoc invocation of tasks and sub-processes. The different processes of a tasks and sub-processes can be called either sequentially or non-sequentially (i.e. scheduling every process with a different frequency).

The NBO-Process-Module is composed of 3 functions:

- Dependency check
- Tracking process status (Started/Completed)
- Calling classes that perform the main



The HP NBO orchestration allows to stitch analytical components together to use them as a package.

Visualization engine

The visualization engine is a dashboard showing all relevant data of the platform, in particular it allows to visualy analyze the recommendations efficacy.

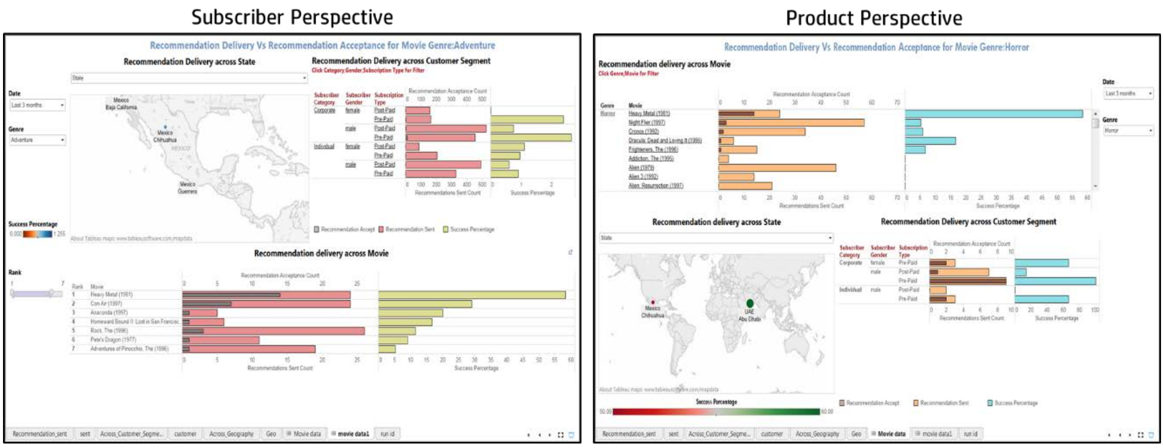


Figure 7 - Example of HP NBO dashboards for video recommedation analysis

How it works

HP SPS NBO is a staged machine performing several steps to produce its result. In the picture below the overall process is shown:

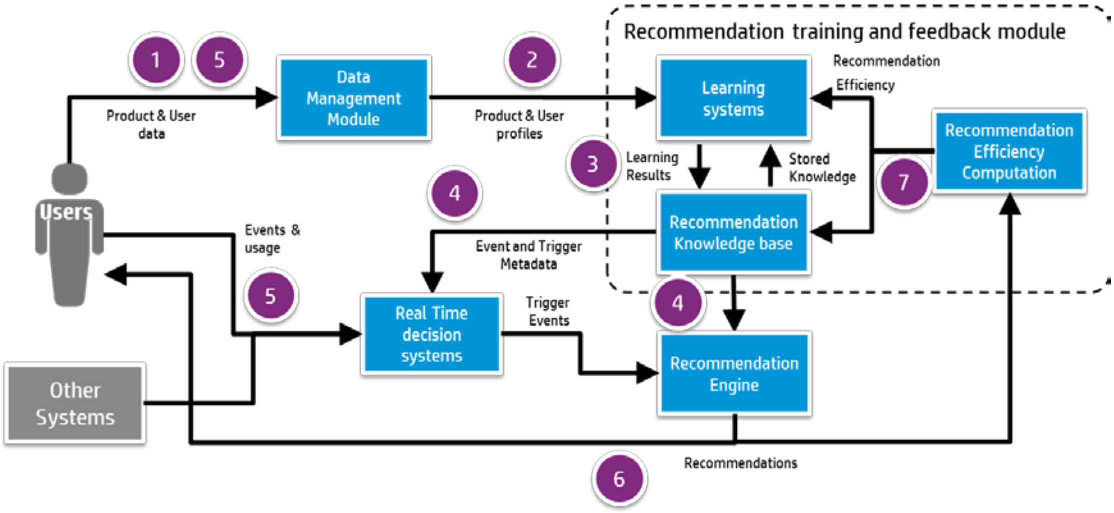


Figure 8 - HP NBO system's overall flow

1) At the beginning, product's and user's information is loaded in the Data Management which will create the product and user profile.

2) Part of the data (test set) is used inside the learning system (a submodule of the Recommendation Training and Feeback module) to refine the recommendation engine.

Learning System
It tests different types of recommendation schemas, and stores the results in a knowledge base. The best recommendation schemas are used to recommend products to subscribers. The learning system can split the data into training set and test set. After training the recommendation model using training set, recommendations are made for subscribers in the test set. The effectiveness of each recommendation model would be computed by comparing the results of the test set recommendations with information provided by the test set.

---

3) The results of the Learning system are stored in the NBO Knowledge base.

4) The selected paramenters - the same which optimize the recommendation engine performances) are loaded in the recommendation engine; while the triggering events – which are the events for which we want to run a recommendation - and the metadata are loaded in the Real Time decision systems.

Real Time decision systems
It identifies events or group of evnets which trigger the recommendation system to compute and send different types of recommendations to particular set of subscribers at particular time.

---

5) The system is ready for production. As soon a trigger event or group of events happen, the Real Time Decision sytem sends a recommendation request to the recommendation systems. The trigger event can be a User's request or action but can also be a system generated request (f.e. activate a campaign for all the user in a particular area).

   The new user data are updated in the systems throught the Data Management module.

6) The Recommendation engine computes the request and send the recommendation back to the user and to the Recommendation Efficiency computation component.

7) The Recommendation Efficiency computation component computes the effectiveness of the recommendations made to the subscribers. The effictive results are sent to Learning systems and to the knowledge base to retrain the models

Conclusions

HP SPS NBO solution brings marketing to a next level, enabling customer's one-to-one, personalized and preference-based marketing. With HP NBO, companies can turn themself in fully Customer-Centric organizations and maximizing their revenues.

The HP NBO solution is ready to use, as its analytic models have been already created in the solution. This allows Company to have a extremelly fast implementation time and time to market.

Learn more at

hp.com/go/TelcoBigData

About the authors

Andrea Fabrizi is the Director of Telco Big Data and Analytics business unit and he is responsible for the development and the commercialization of big data and analytic products for telecommunication industry. Andrea has a degree in Physics and +25 years of experience in the telecommunication industry. Andrea can be reached at andrea.fabrizi@hp.com

Tamer Banoub is the Worldwide Manager of Telco Big Data and Analytics solutions practice and is responsible for the research and development , deployment of big data and analytic solutions for the telecommunications industry. Tamer has a Master's degree in Computer Science and Engineering and 20+ years of experience in the telecommunications industry across consulting, architecture and leadership positions. Tamer can be reached at tamer@hp.com

Sign up for updates
hp.com/go/TelcoBigData

Share with colleagues

Rate this document

4AA4-TBDA-ENN, November 2014