RECOMMENDATION IN E-COMMERCE
“We are leaving the age of information and entering the age of recommendation”

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The massive adoption of the Web as an e-commerce platform has led to a fundamental change in the way that businesses of all sizes interact with their customers. Whereas potential access to a larger, more diverse customer base is generally viewed as an opportunity, this can also represent increased competition. The stakes are high and businesses have to develop sophisticated strategies to attract and retain customers.

Rather than focusing on “touch points” during the marketing and sales processes, businesses are using intelligent algorithms and social technologies to form meaningful, ongoing relationships with customers; these can involve frequent online interactions, often employing social channels. Engaging with customers is no longer a series of one-off experiences; it’s an ongoing dialogue. Surprisingly, these ongoing dialogues resemble dialogues between people: they usually express intent and achieve their goals by building on trust and open relations.

Luminis believes that acknowledging and understanding the human factor in on-line dialogues is crucial for success; we try to understand these ongoing dialogues using the following model:

\[\text{Figure 1: a model for on-going, online dialogues.}\]

\[^1\] Since 1979 when Michael Aldrich pioneered e-commerce, the industry is now estimated to be more than a trillion Euros and is expected to quadruple by 2016.
When designing an on-line dialogue, there are two specific areas that are of critical importance: “How to listen to customers in on-line dialogues” and “How to provide customers with a personalized, relevant experience”. Both of these questions require increasing insights into the individual or the group with which an online dialogue is engaged.

This document summarizes how recommender technology can be used to create a personalized experience for customers. It explains the different types of recommender systems and highlights the impact of applying these systems in an e-commerce architecture.

**The Added Value of Recommendation in e-commerce**

The use of recommender systems in an e-commerce environment can impact financial performance as well as the intensity of the dialogue with customers. More specifically, recommender systems can enhance e-commerce dialogues in three ways:

1. **“Conversion”: Turning Browsers into Buyers**
   Increasing the proportion of visitors to a Web-site that make a purchase. Recommender systems help consumers find items that best fit their interests and inclinations; these may include unplanned purchases driven by serendipity from the recommendations made.

2. **By increasing Cross-sell**
   Recommender systems improve cross selling by suggesting additional products or services to customers. If the recommendations are good, the average order size increases. For instance, a site might recommend additional products in the checkout process, based on those products already in the shopping cart.

3. **By building loyalty**
   In a world where competitors are only a click away, building customer-loyalty becomes an essential aspect of business strategy. Recommender systems can improve loyalty by creating a value-added relationship between the site and the customer. Each time a customer visits a website, the system “learns” more about that customer’s preferences and interests and is increasingly able to operationalize this information to e.g. personalize what is offered. By providing each customer with an increasingly relevant experience, a corresponding improvement in the likelihood of that customer returning is achieved. Ultimately, the depth of insight gained into a customer’s preferences and interests can be so great that even if a competitor were to launch an identical, or even superior system, the customer would need to spend an inordinate amount of time and energy “teaching” the competitor to offer a similarly attractive experience.

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2 Horace Walpole coined the term ‘serendipity’ in 1754, describing this as “making discoveries by accident and sagacity of things that one is not on quest of”

3 See also: http://hbr.org/1995/03/do-you-want-to-keep-your-customers-forever/ar/1
Recommender systems explained

Recommender systems have the effect of guiding users in a personalized way to interesting objects in a large space of possible options. To realize this, recommender systems use a number of different technologies. We can classify these systems into two broad groups:

1. **Content-based recommenders**
   Content-based recommenders make recommendations by matching a description of an item (a general term for any kind of content or information, e.g. a book, video, or event) and a profile of the user’s interests.

2. **Collaborative filtering systems**
   Collaborative filtering systems produce user specific recommendations of items based on patterns of ratings or usage (e.g. purchase) without need for exogenous information about items or users.

The following section contains a more precise description of the recommender types.

**Content-based recommender systems**

A content-based recommender makes recommendations to a user by matching the description of an item and the profile of the user’s interest. There are three important aspects to a content-based recommender namely, “the matcher”, “the item descriptions” and “the user profile”.

![Diagram of content-based recommendation](image)

Figure 2: content-based recommendation.
“The matcher” can be based on a variety of algorithms. Apart from rule-based algorithms, most algorithms stem from the well-established domain of information retrieval theory. Selecting the most suitable algorithms is based on the context of the website’s specific purpose and nature.

“The user-profile” consists of different types of information:

- A model of the user’s preferences, i.e. a description of the items-types that interest the user. There are many possible alternative representations of this description, but one common representation is a function that predicts the likelihood that the user is interested in an item. For efficiency purposes, this function may be used to retrieve the number of items most likely to be of interest to the user.

- A history of the user’s interactions with the recommender system. This may include storing the items that a user has viewed together with other information about the user’s interaction, (e.g. whether the user has purchased the item or a rating that the user has given the item). Other types of history may include queries made by the user as well as returned purchases together with the reason(s) for returning the purchase.

Filling a user’s profile or “learning a user model” can be achieved by using different techniques including rule-based algorithms, decision trees and traditional machine learning algorithms.

Item descriptions are stored in Product Data Management (PDM) systems\(^4\) and can be access using a prescriptive product-model. PDM systems are not only essential to the working of a Recommender system, but also promote items to be found and catalogued in external e-commerce sites, and search systems e.g. being found by Google (so called googleification\(^5\)) is of increasing importance.

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\(^4\) Product Data Management: see also http://en.wikipedia.org/wiki/Product_data_management

\(^5\) Googlification: see also http://www.scoop.it/t/the-googlification-of-everything
Collaborative filtering systems

Collaborative Filtering systems make recommendations exclusively based on knowledge of users’ relationships to items. These techniques require no knowledge of the properties of the items themselves.

Within Collaborative Filtering (CF) we distinguish two important classes, user-based and item-based, supplemented with several optional variations.

User-based CF algorithms start by finding a set of neighboring users who purchased or rated items overlapping this target user’s purchased or rated items. These neighboring or “like-minded” users are found using so-called “user similarity values”. The similarity of two users can be calculated in differing ways, whereby the optimal approach may vary, depending upon the recommendation context. After calculating user similarities, the algorithm aggregates the items consumed by the most similar users, eliminates those items that the target user has already purchased or rated, and recommends the remaining items to that user.

An alternative to user-based CF techniques is item-based CF, a technique which compares each of the user’s purchased or rated items to related items and then combines the most similar items into a recommendation list. The measurement of item similarities may be performed with the same metrics as used to compare user profiles with user-based CF. This item-based technique is often used to calculate recommendations for big online shops, where the number of users is much higher than the number of items.

Figure 3: a schematic overview of collaborative filtering.
The Long tail

The need for recommender systems finds its roots in the "long tail" phenomenon. Brick-and-mortar stores have limited physical space, and can therefore only display a subset of all the choices that exist. On-line stores however, can make anything that exists available to the customer. Thus, a physical bookstore may have several thousand books on its shelves, but e.g. Amazon offers millions of books. A physical newspaper can print several dozen articles per day, while on-line news services offer thousands per day.

Recommendation in the physical world is fairly simple since it is not possible to tailor the store to each individual customer. Typically, a bookstore will display only those books that are the most popular and a newspaper will print only those articles that most people will be interested in. In the first case direct sales results control the choices, in the second case, this is done based on editorial judgment.

An important distinction between the physical and on-line worlds can be attributed to the "long tail" phenomenon, and it is illustrated in the figure below:

The long tail shows the relation between popularity (the number of times an item is chosen) and products. The left-hand side, or "head", lists the most popular products, whereas the right-hand side, or the "long tail", contains the least popular products. Brick-and-mortar stores are geared-up to only provide the most popular items, listed in the head, while the on-line stores can provide the entire range of items: the tail as well as the popular items. This phenomenon is one of the distinctive values of on-line stores for consumers.
Because users of an on-line store would wish to view all of the items available in that store, there is a need to recommend selected items to individual users. This means that recommenders must be designed to recommend items both from the head as well as the long tail.

**Luminis Recommendation Services**

Making recommendations in an e-commerce environment can be challenging because:

- A retailer may have huge amounts of data, millions of customers and millions of distinct catalogue items.
- Many applications require that recommendations are returned in real-time, e.g. no more than half a second, while still producing high-quality recommendations.
- New customers are initially characterized on the basis of limited information, typically on only a few purchases or product ratings.
- Older customers may have a glut of information associated with them, based on thousands of purchases and ratings.
- Customer data is volatile: Each interaction provides valuable customer data, and the algorithms must respond immediately to new information.

The Luminis Recommendation Services offer the foundation for the successful implementation of recommendation in an e-commerce environment featuring:

- **Profile services**
  These services are used to define the user model and fill the user profile for content-based recommendation.

- **Content-based recommendation services**
  The content-based recommendation services offer a framework for implementing a content-based recommendation strategy. This framework includes a system for processing item descriptions.

- **Collaborative-Filtering services**
  The collaborative filtering services provides a framework for the implementation of a collaborative-filtering system.
Successful recommendation strategies

In order for any organization to successfully implement a recommender strategy, the following best practices apply:

1. **Recommendation is aimed at improving the customer dialogue.**
   The heart of recommendation lies in gaining insights into your customer. Customers typically require an open, trusted relationship before they will share such insights with you.

2. **Keep the big picture in mind, but start small.**
   A successful recommendation strategy will probably feature a combination of different recommender types, but implementing them all at once is not advisable. Our experience is that starting with a content-based approach is the best first step and that enriching this can best be done on an incremental basis as you acquire an increasing insight into your customers.

3. **Successful recommendation is based on ‘big data’ and should not be underestimated.**
   Building user profiles, getting control of product data and integrating with existing customer history are a few examples of ‘big data’ problems that should be taken into account when implementing a recommendation strategy. It is important therefore, to understand that the success of recommendation lies for a large part in the accumulation of historical information that may require time to gather.

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**Figure 5: an overview of hybrid recommendation strategies.**

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6 Big Data, see also: [http://en.wikipedia.org/wiki/Big_data](http://en.wikipedia.org/wiki/Big_data)
Implementing recommendation services

The Luminis Recommendation Services are based on Amdatu\(^7\). Amdatu enables the development of cloud-based systems using a modular architecture and is available in both hosted and Open Source distributions.

In line with the Amdatu architecture, the Luminis Recommendation Services runs in a hosted cloud-setup and can be integrated using REST-services\(^8\). Using various adapters - either of the shelf or custom made- the Luminis Recommendation Services can integrate with Product Data Management Systems, Fulfilment systems (ERP) and Customer Relation Management Systems.

![Diagram: a typical recommendation deployment.](image)

Figure 6: a typical recommendation deployment.

More Information?

For more information about the Luminis Recommendation Services, you can either contact the nearest Luminis offices or the authors of this document. They can be reached at: hans.bossenbroek@luminis.eu and hans.gringhuis@luminis.eu

\(^7\) Amdatu, see also: http://www.amdatu.org

\(^8\) REST, see also: http://en.wikipedia.org/wiki/Representational_state_transfer