Theme assignment 4: Analyse the business opportunities of a new AI application. Sales training software powered by AI/ ML.

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1. Introduction

Many organisations need sales operations in order to growth the business. These contribute significantly to growing revenue and improving sales productivity. According to Heiman, "nearly 66.7% of organizations have dedicated sales operations teams, with a further 9.9% intending to create one in the next year" (CSO Insights, 2020).

However, organisations find it difficult when they need to provide the suitable training for every sales professional in the organization. Concretely, trainings and onboardings are highly challenged by the regular sales back-office activities which are picked up by the finance, sales managers or IT departments.

Most of the times, a considerable amount of these tasks is left undone due three factors: time constrain, resource scarcity, and lack of automation. However, these back-office functions are essential to optimize the performance of salespeople once they put hands on the job. Quick (2018) argues that "while new hires sit in training, sales are lost, and the customer experience suffers." Shortly, the onboarding time can be wasted if it is not managed correctly.

Trainings and onboardings require a certain amount of information that is too big to retain. In the classical onboarding and training processes the employee gets a lot of disjointed information without context. As a result, the employee ends up not knowing what is relevant in the field. In the end, as Quick (*ibid.*) asserts, "sales agents are the ones who have the most questions, however, they are the least equipped to find the right answers or support."

The complexity of these processes resides in the lack of synchronization of the pieces that arm the new sales agent with the right tools to perform optimally. The wide range of personalities of salespeople add complexity to this problem. This wide variety require that the employer customize these processes according to the sales agent needs.

The old mentality of onboardings and trainings hurts the other departments, especially the Human Resources department, when onboarding that new hire. This interrupts these departments' activities. In addition, failing in other activities such as setting up new sales reps' accounts, emails and credentials kills the new sales rep motivation and believe in the company.

This paper proposes a business model of a system that automates the training and onboardings for sales teams. These system focuses on automating these back-office tasks by use machine learning, ML, algorithms, concretely, recommender systems. The automation of these tasks can deliver a lot of value especially for small and medium enterprises that are growing their sales teams. This value proposition dwells in its ability to: 1) customize training and onboarding processes; 2) optimize the time taken by these tasks; and 3) simplify objectives and benchmarks with other processes.

2. **Mind Map**

Figure: Business opportunity of an AI application

3. Business model

Development of an Automated API for Sales teams

What's the offering?

Automated API for the optimization of training and onboarding processes for sales teams.

How will you monetize the offering?

Quote per company size and number of licenses. This will depend on the number of people, training / onboarding time, and infrastructure build-up.

How will you sustain it?

Investment in organizational-level software
Resell activity for CRMs
Matchmaking between users, industry and trends

Mission, Objectives, Strategy, Tactics:

Mission → Build the next generation of top-notch sales teams in the Nordics.

Objectives → Organic growth in Finland with expansion in the rest of Scandinavia

Strategy → Recommender systems

Tactic → Automate Back-office processes using AI and machine learning architectures.

Business Architecture

The preparation of the next generation of sales force in the Nordics. Optimal onboardings and trainings. Also, a reseller centre for other software-as-a-service (SaaS) providers

Business foundation

Mentors and Software powered by AI and ML

Competitive Strategy

Multidisciplinary mentoring and a dynamic model. Cooperation with other SaaS vendors

Profit formula

Price-quote
Charge 10% per resell of other CRMs

Value proposition

Optimization of trainings and onboardings
Cost effectiveness

Revenue model

Onboarding and training services
Reselling

Customer generation

Network organic growth and outbound sales strategies

Competitive advantage

International input

Strategic advantage

HQ in Helsinki
Remote Training

4. Theoretical approach: Recommender systems for the business model

Recommender systems incorporate a type of techniques and algorithms that suggests relevant content to the user (Seif, 2019). These items are as relevant to the user as possible, so that the user has more engagement to that content. Platforms such as Youtube, news sites, or online stores make use of recommender systems to present tailored items to the users.

Recommender systems work in a way that the content is ranked according to relevancy. Theis ranking is based on historical data, which enables the system to show most suitable items to the users. These systems are divided into two main categories: collaborative filtering and content-based systems. The former is also divided into other two subcategories: model based and memory-based systems. These subcategories will not be explained since it does not concern this business model at the moment. On the other hand, content-based methods count with two approaches: 1) description of content and 2) building content and item profiles. These will be explained since the

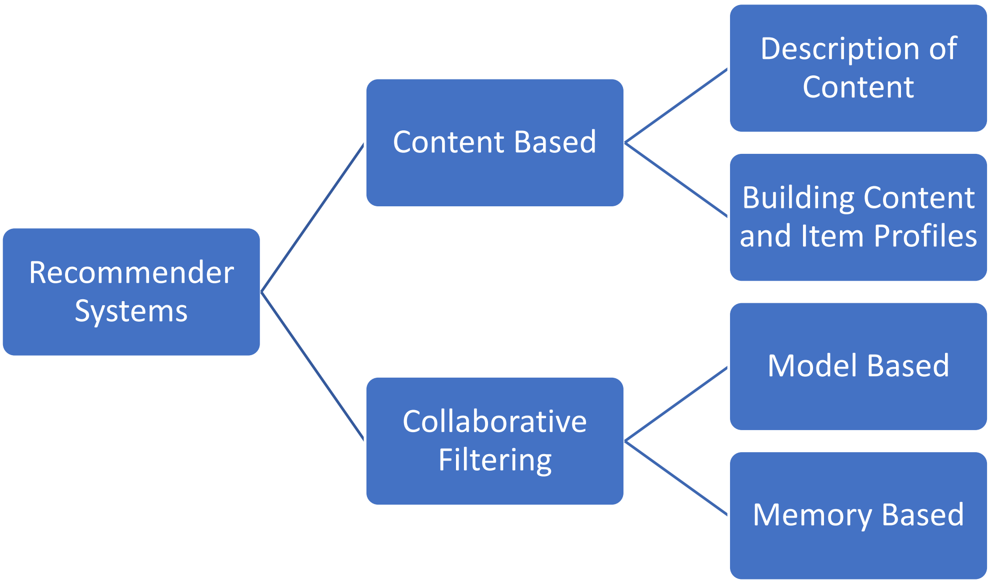

Figure: a tree of the different recommender systems

Collaborative Filtering.

This method consists in the previous interaction between the user and a large selection of items. Therefore, the input of collaborative systems will consist of all historical data of the user's interaction with target items (Korbut, 2017). Shortly, the core idea is that that data should be enough to make predictions. This method will be really convenient when providing those refreshing trainings in a since there will be more user historical data available in the system.

Content-based

For the onboardings, this service application I will be using a content-based recommender system. This uses addition information about the user and / or items to make predictions. For instance, data like age, sex, occupation, and other relevant data will allow the system to make better predictions. In this way, the software can predict what content is the most suitable for the user.

This method is more similar to classical ML, in the sense that it builds features based on user and item data to make predictions. Therefore, the data input will be the features of the user and the features of the item required by the user. As a result, the output will be a prediction of what would be the more relevant for the user at a first glance, regardless of whether or not the user would like or dislike the item.

- Description of content

According to Luck (2019), the description of content approach is a system that recommends anything similar to an item the user pointed before. This system first finds the similarity between all pairs of items, and then uses it the most similar items pointed out by the user.

This similarity will be processed by the TF-IDF, Term Frequency-Inverse Document Frequency, vector. TF.IDF is a vector of Natural Language Processing, NLP, used in information retrieval for feature extraction purposes. Shortly, this vector counts the occurrences of the words in a document, weights the importance of each word, and calculates a score for that document or content.

Term Frequency, Tf, will be calculated with the following formula:

$$\mathrm{Tf(t)} = \frac{\text{Frequency occurrence of term t in document}}{\text{Total number of terms in document}}$$

Inverse Document Frequency, Idf, is calculated:

$$\mathrm{Idf(t)} = \frac{\text{Total Number of documentsy}}{\text{Number of documents containing term t}}$$

Once the TF-IDF values are defined for the tags, a keyword vectors will be created for each of the item. Each row below represents a keyword vector for one item (Shuvayan, 2015):

Content	Analytics	Data	Cloud	Smart	Insights
Content 1	2. 234424	2.4359458	1	1.423754375	2.32538757
Content 2	2. 56828435	2.23982449	1.982543	1.304543508	2.23932874
Content 3	3.59436985	3.2048y214	1.239743	1.304704533	1.23104853
Content…	1.43589536	4.1239644	4.2905487	2.047604593	2.23094328
Content *n*	2.124o8895	7.3645400	5.9049878	2.24043294	4.21+34720

Table: a TF-IDF vector

To compare the similarity of the item vectors, various methods can be used such as: Cosine Similarity; Euclidean Distance; or Peason's Correlation.

- Building Content and Item Profiles

This method supports attributes from items the user interacts in order to recommend similar ones. This approach depends on the user previous choices, avoiding any kind of cold start during the training or onboarding. This method will use the item category to build user and item profiles. For instance, the employee reads or watches a particular study or market analysis during the training or onboarding time. The system will recommend other content related to that category.

Luk (2019), explains that in this approach the content will be rated based on the user's preference (user profile). On the other hand, the genre of an item, defined by its implicit features, will be used to build the item profile. The item score will be predicted using both profiles and the recommendations. As, in the description of content approach, TF-IDF technique is used in this method.

A user's rating table (user-to-item-relationship) and a item profile (attribute-to-item-relationship) are the only two things needed to start executing this approach. Once these two are achieved, the user profile will be created in order to understand the attributes the user prefers. To finish, the user profile will allow to predict the item score of a particular user based on the user profile and the item profile.

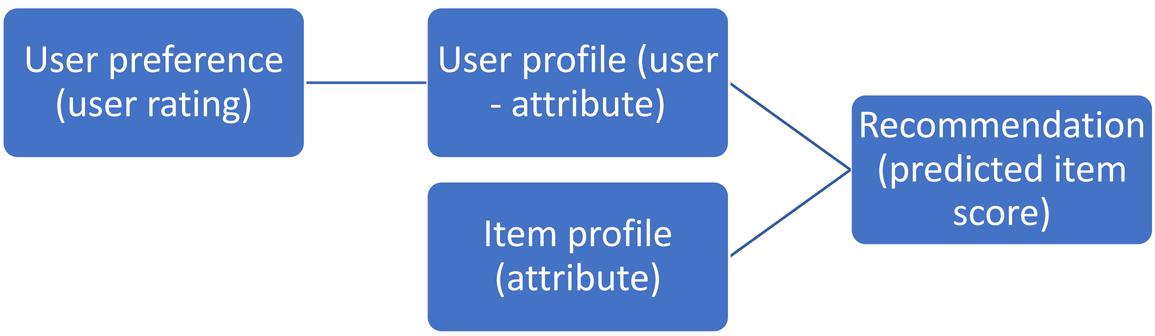

Figure: Building Content and Item Profiles approach

5. Implementation and scalability

This software for trainings and onboardings can be implemented as an Aggregated Programme Interface, API, to other Client Relationship Management, CRM, systems. Thus, the implementation of this software in the sales team will be led mainly by the sales management team in cooperation with the IT department.

During this implementation, other processes that converge with the sales team's activities will be investigated and revisited in order to give harmony between this and previously automated processes. To consolidate this, and engagement strategy should be set in order to encourage the sales team to use it. To crystalize the implementation, a monitoring practice will be held in order to measure the performance of this software, and to allow the program itself to gather feedback in order to reach an optimal performance.

This software and its tasks are mainly directed to sales departments. However, it can be scalable to other areas such as marketing, human resources or management. All the surveys and data inputs requested for the right implementation of this software will follow the EU legislation on General Data Protection Regulation, GDPR.

6. References

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