Identification of Distinct Usage Patterns and Prediction of Customer Behavior

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Abstract. The given BPI Challenge 2016 provides a case study based on a real-life event log. In this report, we analyze usage data from IT systems of the Dutch employee insurance agency (UWV). The data comprises information about customer demographics, click data describing their behavior when using the agency's website, and data from customer service systems. We identify distinct usage patterns, report on the change of those patterns over time as well as on cause-effect analyses explaining when customers deviate from standard procedures. Moreover, we present a prediction approach based on deep learning algorithms that helps to determine future events for running customer sessions. As a result, some recommendations for the UWV are derived in order to increase the user experience and decrease expensive communication-channel transitions.

Keywords: process mining, process analysis, usage pattern identification, process prediction, deep learning

1 Introduction

The analysis of how customers use the systems and services provided by an organization – often called *customer journey analysis* in marketing – is an important activity to gather insights into the specific requirements and preferences that drive different customer groups. It can help to segment the customer basis according to various properties, ranging from demographics like age or gender to behavioral characteristics, for instance *heavy users*, *casual users* etc. Results from such analysis can help to better understand individual customer demands, to improve existing system and service interactions, and eventually to enhance overall customer experience and satisfaction. As these aspects depict an important distinguishing feature for customers when choosing between service providers, they have traditionally been of great interest in competitive market situations. However, in recent years providing satisfying customer experience also gains in importance for governmental institutions.

In this paper, the setting is defined within the scope of employee insurances and labor market and data services in the Netherlands. The data at hand comprises user interaction data from different IT systems, which is operated by the Dutch Employee Insurance Agency UWV that in turn is commissioned for the implementation and operation of respective services by the Ministry of Social Affairs and Employment (SZW). For that purpose, UWV operates two major IT systems: (1) the website *www.werk.nl*, which serves as a central contact point for matching people looking for a suitable job with currently available positions, and (2) the so-called *werkmap*, which serves as an instrument to keep track of customers' obligations and manage associated activities.

According to the problem statement formulated in the context of this year's BPI Challenge 2016, UWV is interested in the way both the site www.werk.nl and the Werkmap systems are used. In particular, the following questions have been posed:

1. Are there clear distinct usage patterns of the website to be recognized? In particular, insights into the way various customer demographics use the website and the Werkmap pages of the website are of interest.
2. Do the usage patterns of the website by customers change over time? Do customers visit different pages when they start using the website versus when they have been using the website for some time? How does the usage change over time?
3. When is there a transition from the website to a more expensive channel, such as sending a Werkmap message, contacting the call center or filing a complaint? Is there a way to predict and possibly prevent these transitions?
4. Does the behavior of the customers change after they have send a Werkmap message, made a phone call or filed a complaint? Are customers more likely to use these channels again after they have used them for the first time? What is the customer behavior on the site after customers have been in contact through the Werkmap or by phone?
5. Is there any specific customer behavior that directly leads to complaints?
6. Finally, we challenge the creative minds, to surprise UWV with new insights on the provided data to help improve the experiences of our customers when using the website.

For most questions, there is a clear focus on usage behavior and on customer interactions with the different IT systems. As a consequence, temporal aspects of the data – for instance *when*, *in which order* and *over which period in time* did an event occur – need to be considered in order to answer those questions.

The paper is organized as follows. Section 2 provides a brief overview to the data description and analysis tools used in the current paper. Section 3 addresses the identification of distinct usage patterns. The change of usage patterns is discussed in the Section 4. Section 5 examines the applicability of deep learning approach to predict the next process event. Exploratory analysis about more expensive channels are discussed in Section 6, while section 7 introduces the usage patterns that lead to complaints. Finally, section 8 gives a short summary and concludes the report.

2 Data Description and Software Tool Chain

The data used for the analysis described hereafter was published in the context of the Sixth International Business Process Intelligence Challenge (BPIC'16).[1] It comprises five different datasets originating from multiple sources in an internal process of the Dutch Employee Insurance Agency UWV, a facility which provides employee insurances and market labor services in the Netherlands. Table 1 provides an overview of the individual datasets along with a brief description and some basic statistics. All data files were provided in plain *.csv* format. For the sake of brevity, datasets are numbered consecutively for easier reference throughout this paper.

Table 1. Software frameworks and tools employed for data preprocessing and analysis.

Name	Description
Dataset 1 [1]	Customer interaction data from website *www.werk.nl* where customers do not have logged in to the site, i. e. they are anonymous to the system as no demographic data is available. The dataset contains additional information about visited pages, timestamps for events, and details on technical behavior of the website.
Dataset 2 [2]	Interaction data from registered customers who have logged in to the website. Demographic (age category and gender) and organizational information (responsible resources/offices) is available in addition to the data from dataset 1.
Dataset 3 [3]	Meta information about questions asked by customers. Besides customer data the question is described by theme, subtheme and topic depicting predefined categories that a customer can specify when posting their question.
Dataset 4 [4]	Data from the *Werkmap* system that is used as an internal instrument to keep track of customers' obligations. It provides information on when customers sent messages to UWV, the message type and the ID of the handling channel.
Dataset 5 [5]	Meta information about complaints filed by customers, where provided data fields correspond to Dataset 3.

The data focuses on customer interactions with UWV's IT systems in a specific process ("unemployment benefits process") where both *passive* interactions – a customer using the website without the need for UWV to interfere – and *active* interactions – e. g. a customer requesting support by writing a complaint – are captured. In total, customer interaction data from an eight-month period is provided. Regarding the language, the datasets contain both Dutch and English text. While for some data fields, entries are provided in both languages (e. g. for *theme*, *subtheme* and *topic* in datasets 3 and 5), others are only provided in a single language (e. g. *page_name* in dataset 1 and 2 which describes the name of the webpage a customer visited).

To efficiently inspect, analyze, and understand the data, all datasets were loaded into a unified local database. This way, slicing and extracting relevant data sections and joining information that was distributed across several sets for a comprehensive analysis were largely facilitated. For data discovery and preprocessing of high-volume

[1] http://www.win.tue.nl/bpi/doku.php?id=2016:challenge

data, an additional in-memory database was employed. A variety of tools was then used to investigate the data from different perspectives in order to provide valuable insights and answers to the questions formulated in the challenge. While descriptive analytics were primarily used to describe static aspects and distributions of the data, analysis have been complemented by the application of methods to consider temporal aspects of data. The following table provides a summary of the software frameworks and tools that have been applied for data preprocessing and analysis.

Table 2. Software frameworks and tools employed for data preprocessing and analysis.

Framework/Tool	Application purpose
Disco	Process mining, process discovery, behavior analysis
Java	Data preprocessing, data querying, data conversion
ProM 5.2	Sequence clustering, data conversion
SAP HANA In-memory database	Data preprocessing, descriptive analytics, data slicing, calculation of metrics
PostgreSQL	Local database for lightweight data preprocessing
R and RStudio	Data discovery, descriptive analysis, data manipulation, graphs
Tensorflow	Deep Learning
Weka	Machine Learning, regression analysis

3 Challenge 1: Distinct Usage Patterns for www.werk.nl

This section provides answers to the following question: *Are there clear distinct usage patterns of the website to be recognized? In particular, insights into the way various customer demographics use the website and the Werkmap pages of the website are of interest.*

As a first step, we define the concept of usage patterns that will be the basis for subsequent description: A *usage pattern* is hereafter considered a collection of individual website pages that have been visited frequently by users in order to fulfill certain tasks on *werk.nl* as well as the transitions between those pages. Thus, a pattern captures the characteristics of system interactions conducted by different types of users, e. g. with a specific age categories or any other specific demographic features.

To identify specific usage patterns for different demographic customer groups, we employ process mining analysis in Disco. With respect to the given datasets in the form of clickstream logs, process mining can leverage causal and temporal order of frequent occurring sequences. As demographical information about customers is only contained within *dataset 2*, we focused on this dataset when identifying distinct usage patterns. Therefore, the following steps were conducted each segment:

1. Separation of *dataset 2* into segments
2. Import of segmented data into Disco
3. Extraction of most frequent events from segments
4. Analysis of reduced event sets
5. Derivation of usage patterns

Step 1: Separation of dataset 2 into segments. In order to segment the entire customer base, we concentrate on the data fields containing demographic information, that is the fields *age_category* and *gender*. Therefore, the distinct attribute values for those fields were determined yielding the following sets of characteristics: *gender* contains the values *{M,V}* describing female and male customers while *age_category* comprises the value ranges *{18-29,30-39,40-49,50-65}*. According to those values, subsets of the dataset are then extracted using SQL and saved to individual *.csv* files per segment. Table 3 shows some statistics on those subsets, namely the number of process instances or cases (i. e. individual customers) and the total number of events per segment.

Table 3. Segmentation of customer basis with respect to demographic features.

Segment	Cases	Events
#1 Age category 18-29	105.832	1.102.717
#2 Age category 30-39	133.310	1.427.763
#3 Age category 40-49	158.687	1.774.864
#4 Age category 50-65	262.490	2.848.044

While the sum of cases for the segmentation by age should match the sum of cases for the segmentation by gender, there are some missing values for the *gender* field such that those number slightly differ.

Step 2: Import of segmented data into Disco. In the next step the segment files were separately imported into Disco. The following import settings were applied for all files: the data field "session_id" was set as *case id*, "page name" was set as *activity*, "timestamp" was matched to the *timestamp* field provided by Disco and "user_id" was matched to the *resource* field.

Table 4. Filtered activities representing the most frequent activities for segment 1.

Activity	Absolute Frequency	Relative Frequency
taken	326.294	29,59%
mijn_cv	166.920	15,14%
home	83.778	7,60%
vacatures_bij_mijn_cv	82.588	7,49%
mijn_berichten	79.481	7,21%
vacatures_zoeken	67.217	6,10%
aanvragen-ww	59.339	5,38%
inschrijven	36.113	3,27%
mijn_werkmap	28.967	2,63%
mijn_sollicitaties	27.268	2,47%
mijn_documenten	21.237	1,93%
werkmap	18.882	1,71%
wijziging_doorgeven	14.026	1,27%
vragenlijst-uwv	13.058	1,18%

Step 3: Extraction of most frequent events from segments: Due to the high number of cases and events, importing the individual segments according to step 2 resulted in a very large process model (so-called "spaghetti model"). To reduce this preliminary all-encompassing model, only the most frequent activities were further considered while others were filtered out by using the build-in features provided by

Disco. Following the idea that usage patterns describe characteristic user behavior, filtering was done with respect to the relative frequency of an activity within the segment dataset. The threshold was set to 1%, i. e. we only considered activities that occurred with a relative frequency of equal to or greater 1%, which resulted in a total number of 13 to 14 activities depending on the dataset. Table 4 exemplarily shows the results for segment 1. While the lists of activities slightly differ for each segment, the was a large overlapping, for instance *taken*, *mijn_cv*, *home*, and *werkmap* appear across all segments.

Step 4: Analysis of reduced event sets: based on the filtered set of events from step 3, process models were generated. The Disco tool provides additional filtering options regarding the number of activities and scope of paths between those activities that should be included in the model. In our case, those parameters were set to 100% of activities (that is *all* activities from the reduced set) and 0% of paths (meaning only the most frequent ones). Following our definition of a usage model, those values are sound since they lead to the generation of process models which contain only those activities and transitions that are very common. The figures on the next pages show the resulting models regarding the segments.

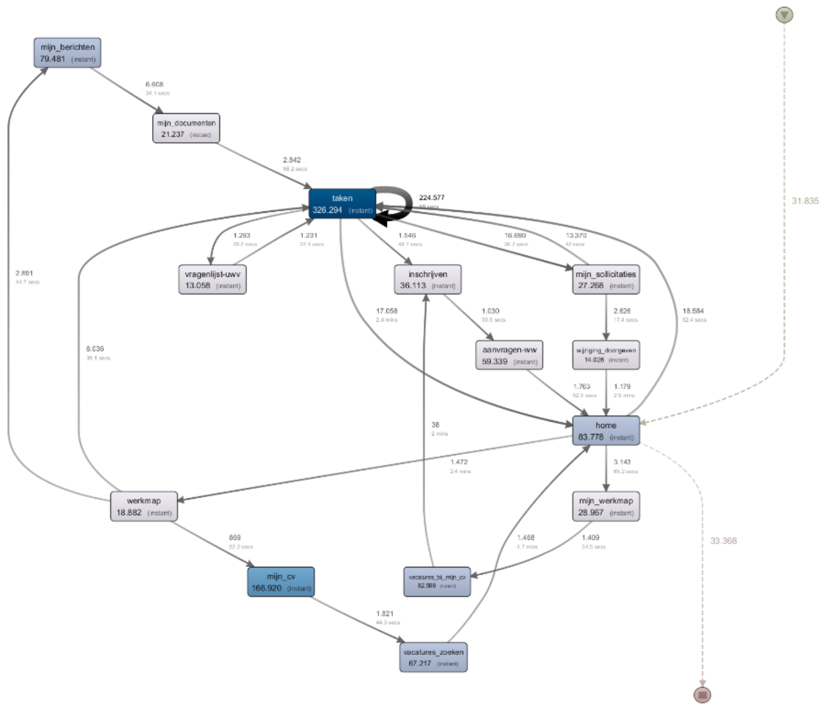

Fig. 1. Process map for segment 1

Step 5: Derivation of usage patterns: to finally derive characteristic usage patterns per segment, the models were compared based on the following features: *start activities* (corresponding to entry pages of the website), the *flow of activities* (corresponding to transitions between pages), and *unique activities* (corresponding to pages typical for a specific segment). In the following, we present key findings along with possible interpretations and recommendations on usability improvements where appropriate:

- While segments 1 to 3 clearly start with activity *home*, this is not true for segment 4 where the *werkmap* activity represents the entrance. Assuming that the home page is the intended starting point that a customer is supposed to use when logging into the system, this deviation is remarkable for two reasons: First, it implies a very different system usage by the customers, because their primary interest is managing the *werkmap* tasks, which significantly deviates from other segments. Second, there is no direct path connecting *werkmap* with the *home* activity, which indicates that the assumed entry point is only used when customers have already performed some tasks.
- To overcome this issue, one measure could be to further investigate the reasons for this behavior: is the information presented on the *home* page not relevant for the interest of these customers? Are there any design or content-specific aspects that impede the customers from using this page? The activity *vacatures* (Dutch for "vacancy", i. .e an open job offering) is frequent in all segments except for segment 1. Instead, customers from segment 1 do look for vacancies (activity *vacatures_zoeken*) but apparently do not find any suitable positions that match their criteria or profiles. For all other segments, the usage pattern that leads to the activity *vacatures* is identical: starting from *home*, customers visit their *werkmap*, then *vacatures* and finally choose to go to *mijn_werkmap*. This may possibly indicate that interesting vacancies were stored in customers' personal work folders for review or application. This issue might indicate that it is hard for younger customers (as in terms of demographics referring to segment 1) to find a suitable job offering. Whether this is problematic or not must be determined from a professional point of view. However, it shows that the focus of young customers using the website is at least in part different from other customers.
- In all segments, *taken* (Dutch for "tasks") is by far the most frequent activity. There is also a high repetition in the form of a cycle, which indicates the activity as the central page of the website to which customers repeatedly return. In addition, there are some noticeable cycles between adjacent activities and the *taken* activity, for instance with *vragenlist-uwv* (list of questions). There is no outgoing path from *vragenlist-uwv* to any other activity than *taken*, isolating the page from others. Thus, questions seem to arise in the context of customers' task and not to be related to other activities. However, this cycle appears in segments 1 to 3 but not in segment 4, which shows that older customers seem to have fewer questions. The reasons for this presumable unintended behavior should be further investigated to derive specific recommendations for system improvement.

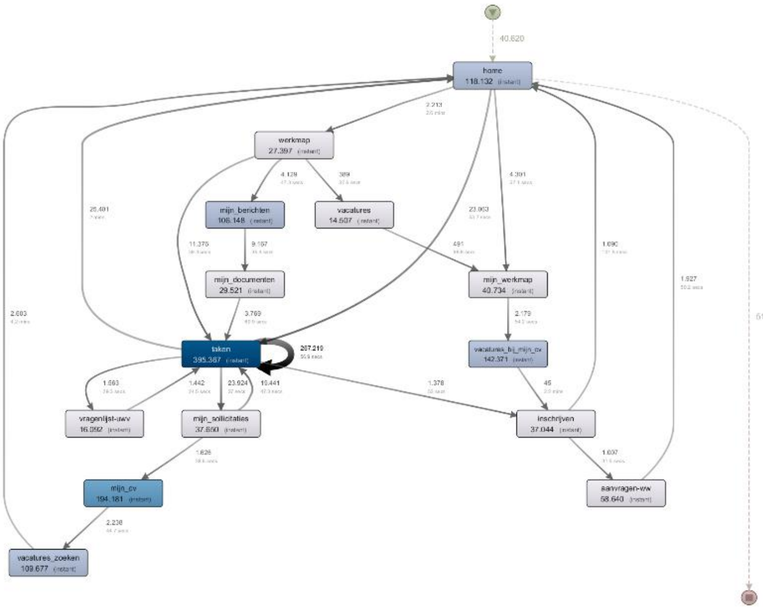

Fig. 2. Process map for segment 2.

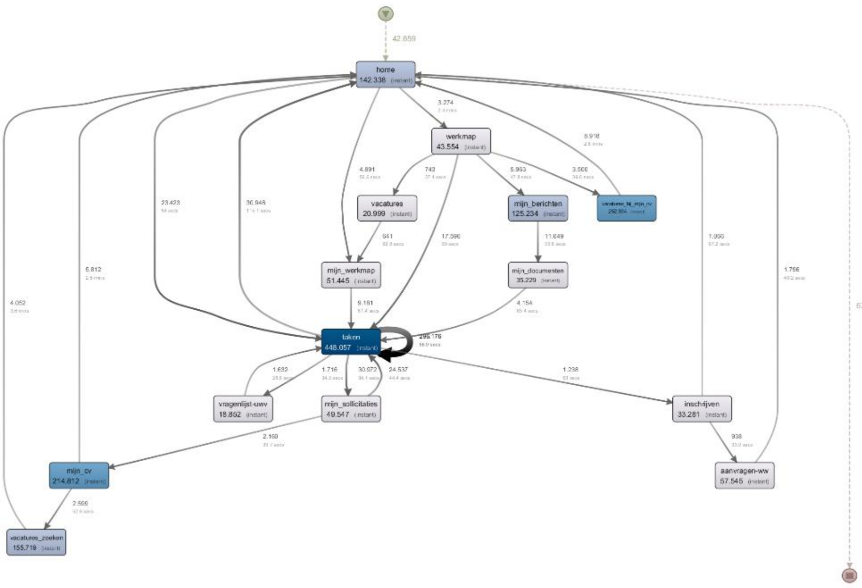

Fig. 3. Process map for segment 3.

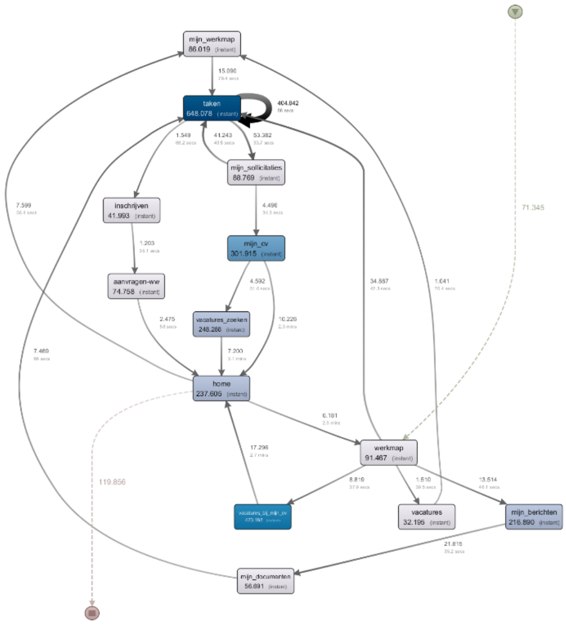

Fig. 4. Process map for segment 4.

4 Challenge 2: Changes of Usage Patterns Over Time

This section provides answers to the following question: *Do the usage patterns of the website by customers change over time? How does the usage change over time?* To investigate the website usage patterns of the customers over time we have sliced the log data of all individual customers in terms of session orders. By using such a categorization, we can identify not only the altering usage patterns over time but also figure out the direction of change, trends and other key measures. Before answering the question about the trends over time, we have to identify what proportion of the customers continues to use the website. Table 5 introduces the number of customer having at least 15 sessions of using the website. The analysis of results suggests that 26,647 users had at least one session which significantly decreased to 14,792 who had at least 15 sessions. From this statistics, we can infer that the users don't tend to use the website after they used it for the first time and this trends continues over time. E.g. Table 5 suggests that 3.54 % of the customers did not use the website again after they used it for the first time. The average drop rate between sessions is 4.12%.

Table 5. Number of customers having at least # of sessions.

Session	Customers	Change
1 Session	26,647	-
2 Sessions	25,705	-3.54%
3 Sessions	24,733	-3.78%
4 Sessions	23,814	-3.72%
5 Sessions	22,896	-3.85%
6 Sessions	21,956	-4.11%
7 Sessions	21,053	-4.11%
8 Sessions	20,143	-4.32%
9 Sessions	19,292	-4.22%
10 Sessions	18,452	-4.35%
11 Sessions	17,691	-4.12%
12 Sessions	16,962	-4.12%
13 Sessions	16,202	-4.48%
14 Sessions	15,435	-4.73%
15 Sessions	14,792	-4.17%

Table 6. Click trend over time (sessions are sorted).

# of Sessions	# of Click Logs	Change	Average # of Clicks per customer pro session
1. Sessions	453,928	-	17.03
2. Sessions	381,350	-16%	14.84
3. Sessions	343,817	-10%	13.90
4. Sessions	309,035	-10%	12.98
5. Sessions	284,811	-8%	12.44
6. Sessions	266,686	-6%	12.15
7. Sessions	248,288	-7%	11.79
8. Sessions	231,511	-7%	11.49
9. Sessions	213,970	-8%	11.09
10. Sessions	201,291	-6%	10.91
11. Sessions	191,186	-5%	10.81
12. Sessions	183,143	-4%	10.80
13. Sessions	171,892	-6%	10.61
14. Sessions	162,147	-6%	10.51
15. Sessions	151,629	-6%	10.25

In Table 6 we have aggregated the number of logs per session sorted according to the time. The first column of this table indicates not the amount but the order of the sessions. E.g. the number of click logs in the first session of all individual customers is equal to 453,928. These results also propose that the number of click logs per session drops over time by decreasing to 151,629 in fifteenth session of all customers. This trend can be considered as reasonable since the numbers customers per session decreases as mentioned above (See Table 5). However, the velocity of negative change in number of clicks is much higher with an average of -7%. Furthermore, to normalize the results we have also calculated the average numbers of clicks by individual customers per session (See Table 6). A decreasing trend in this feature can also be easily observed. On these grounds we can argue that, not only the number of customers using the website decreases over time but also the average clicks per session follows a negative trend.

In order to answer the question how the usage patterns change, we have aggregated the log data of customers beginning from their first session to the fifteenth session and analyzed the visits of website. Figure 5 provides valuable insights into change of website usage behavior over time. We have introduced here the visited webpages with relative frequency higher than 1%. From the underlying diagram we can detect a significant drop in the visit of the “mijn_cv” page. The relative frequency of “mijn_cv” decreased to less than 10% in the fifteenth, which was more than 25% in the first session of users. A significant negative trend is also observed in the visit frequency of “aanvragen-ww” and “inschrijven”.

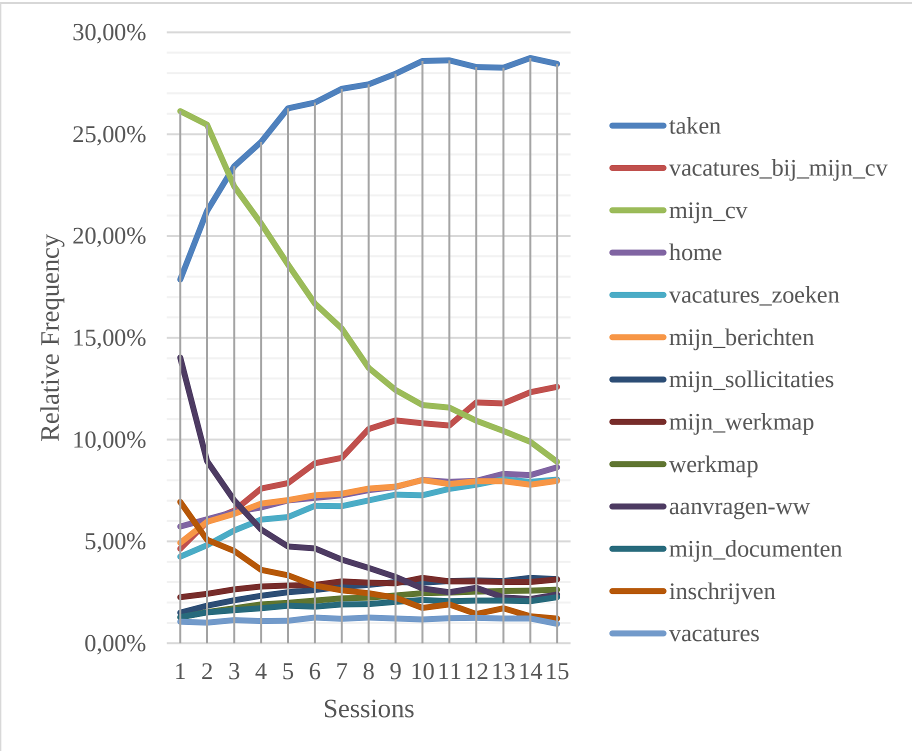

Fig. 5. Change of website usage over time.

In contrast to *mijn_cv*, *taken* follows an increasing preference trend over time. The relative frequency of *taken* has increased from 17.86% in the first sessions to 28.45% in the fifteenth sessions. In other websites such as *werkmap*, *mijn_sollicitaties*, *vacatures_zoeken*, *mijn_berichten* and etc. we can observe an increasing trend however, the amplitude of the change is not significantly high.

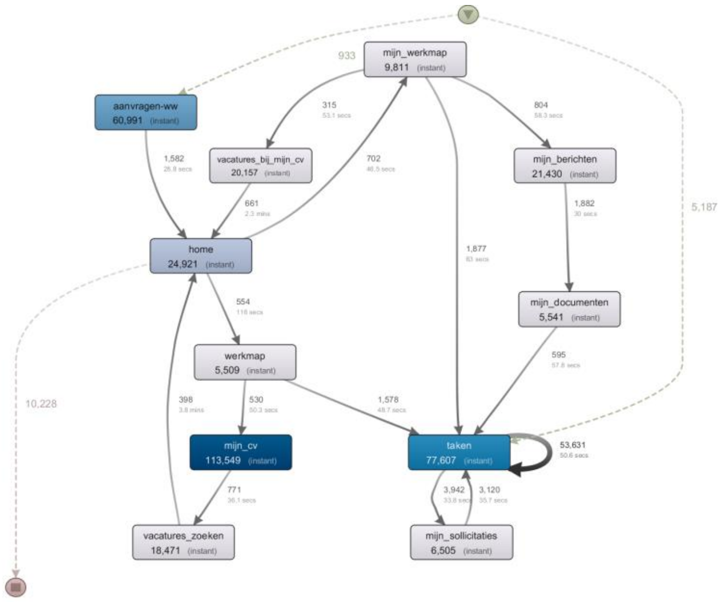

Fig. 6. Process Model representing first sessions of customers.

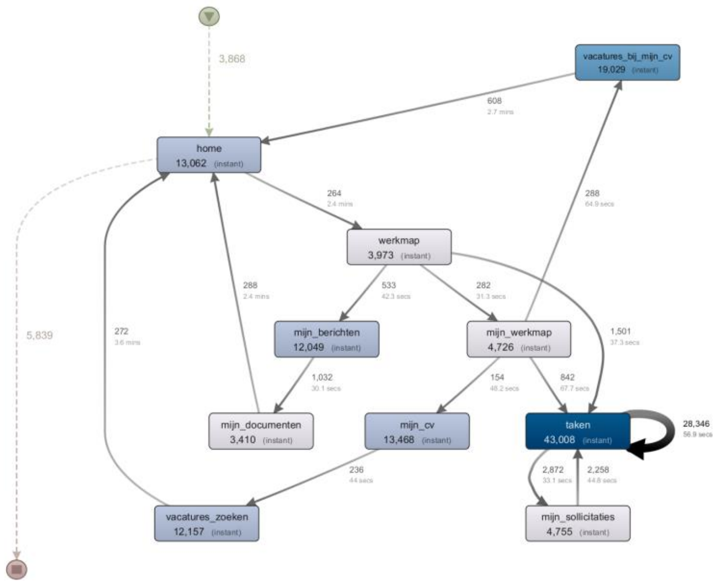

Fig. 7. Process Model representing fifteenth sessions of customers.

In order to identify the changes in the transition between websites we have created the corresponding process maps. Figure 6 and 7 introduce the process models, which represent the first and fifteenth sessions of all users respectively. The number within the process activities are the absolute frequency of visited websites. A significant drop in the number of clicks can also be directly observed here. These process diagrams allow us to observe the process paths evolved over time. A narrow analysis of process models reveal that the sequence of transitions did not change significantly with a few exceptions. E.g., *aanvragen-ww* was one of the most visited website in the earlier sessions, which almost disappeared towards the last sessions. Another example is that there is no link between *mijn_documenten* and *home* in the first sessions of visitors but we can see a high number of direct transitions in the last session.

5 Challenge 3 and 6: Process Prediction

Predicting the behaviour of a user interacting with an information system enables an optimization of the underlying processes. Knowing what step a user is most likely to take next enables individual user assistance, which results in an increased user experience. Furthermore, it allows for estimating and allocating the future resources that are required to effectively accomplish the processes. Since a recent approach in process prediction achieved significant gains in precision by adapting deep learning techniques, we develop a deep neural network and train it using sequences of user actions as training data in order to predict the next user action.

Facing challenge six and three we present a recent machine learning-based approach that enables a real-time prediction of

- the general *user behaviour* and especially
- impending *user-induced transitions* to more expensive channels, e.g. a call centre.

Our approach consists of a (1) pre-processing, (2) a learning stage and (3) an evaluation of our predictor based on the provided log data. In a pre-processing step we first generate sequences of user actions from the specified logs. Then we feed the sequences in the learning stage into the neural network in order to train its prediction capabilities. Afterwards, we evaluate the prediction capabilities in order to assess a real-time customer behaviour monitoring [6].

The predictor is trained on all log entries that are directly linked to a user identifier. Thus, we use the datasets *BPI2016_Clicks_Logged_In*, *BPI2016_Questions*, *BPI2016_Complaints* and *BPI2016_Werkmap_Messages*. Each of these log entries is considered a user's action and is uniquely identified by the user identifier and the timestamp. While we differentiate all click actions, we abstract from specific questions, complaints and Werkmap messages. Hence, a user action is considered a URL of either a click event, a question, a Werkmap message, or a complaint. The Pre-processing of the log entries lead to a total of 785 distinct actions, consisting of 782 URL actions, a question action, a Werkmap message action and a complaint action. For each user we generate a list of actions ordered by the timestamp of the respective action. In order to improve the precision of our prediction, we also add the organizational units handling the customer to a customer's action. Hence, an action, which is processed to the neural network, is represented by a code of the pattern AAA-UUU-WWW. AAA represents the unique identifier provided by the SQL database for each click action, question, complaint and Werkmap message. UUU and WWW represent the original identifiers of the Benefits Office and the Employment Service Office as provided in the log files.

Since our network requires sequences of actions to predict the next action, we concatenate the ordered actions of all customers and split up the concatenated actions each 10th action. We apply the techniques proposed in to translate the obtained sequences into vectors, which then can be fed to the network in order to train it.

We use the deep learning framework *tensorflow* to generate, train and assess our predictor. In particular we model a Long Short-Term Memory (LSTM) network with two hidden layers, each consisting of 128 neurons. Long Short-Term Memory networks have been proven to be effective in order to learn the dependencies between the elements of sequences. Hence, they are well known in the field of speech recognition and time series prediction.

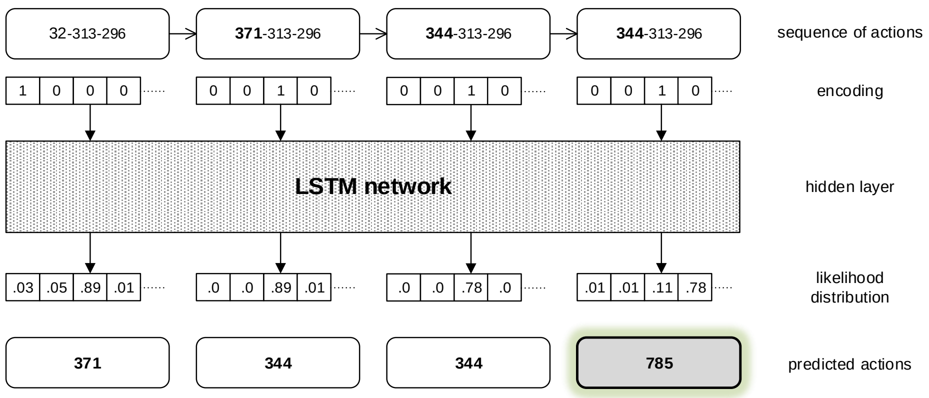

Fig. 8. Feeding action sequences into the neural network

Figure 8 exemplarily shows a processing of an action sequence, which is executed in order to predict the next action, after having trained the network. First, we apply an encoding that maps the sequences to the size of our hidden layers. The obtained vectors of the encoding are then processed within the hidden layers. Finally, the outputs of the hidden layers are transformed into a likelihood distribution over all 785 actions. While training the network on a high-performance consumer GPU took us a couple of days, the retrieval of the customer's next action providing the preceding ten actions is instantly achieved. The evaluation of the prediction capabilities based on the given log data yield an average precision of 64%. Using our predictor and the last 10 actions a customer has taken, gives UWV the ability to predict the costumer's next action with an estimated correctness of 64%.

We now sketch the potential of our predictor based on the asked questions of the customers. We consider a customer's phone call likely to be related to the actions she took on the website, if the phone call is made within an hour after the last click action. This constraint applies for more than 50% of the customers, which asked a question (in total 58,062 customers). Given the fact that an average phone call of the question log data lasts almost 4 minutes, handling these customer requests takes more than 5 months. Monitoring the customers by applying our predictor enables the identification of customers that are likely to contact the call centre. By providing an intelligent assistance to these customers in shape of suggested next steps or a chat feature could significantly reduce a transition to the call centre and reduce the overall effort handling these customers.

However, the fact that our predictor is based on data of a limited period implies that there might be further behaviour patterns, which have not been discovered while training the neural network. Furthermore, our investigation in section 4 shows that the customer behaviour changes over time and new behavioural patterns are likely to evolve. Therefore, a real-world application of our predictor requires also continuously evaluating and improving the prediction model based on recent data.

6 Challenge 4: Transition to more expensive channels

Within this section, we give answers to several questions: *Does the behavior of the customers change after they have send a Werkmap message, made a phone call or filed a complaint? Are customers more likely to use these channels again after they have used them for the first time? What is the customer behavior on the site after customers have been in contact through the Werkmap or by phone?* As the first and third questions are strictly related to each other, we answer these questions in the following two subsections:

6.1 Are customers more likely to use these channels again after they have used them for the first time?

In order to answer this question we have to identify the relevant exploratory statistics about the customers, who used the expensive channels such as sending werkmap message, complaints or contacting the call center. As depicted in the Fig. 1 the total number of contacts via complaints, werkmap and questions are 289, 66,058 and 123,403 respectively. These numbers suggest that calling the customer center is the mostly preferred communication channel by almost doubling the number of werkmap messages. Filling complaints is rarely used by customers as means of communication by corresponding to 0.1% of total contacts.

A further analysis reveals that some customers have used the different channels multiple times as only 226, 16,653 and 21,533 unique customers sent complaints, werkmap messages and questions respectively (See Fig. 10). Considering the averages, we can argue that the customers tend to contact call centers to ask questions (5.73 times) and send werkmap messages (3.97 times) relatively more after they have used them for the first time. This number is 1.28 for sending complaints which implies that with a few exceptions, the customers don’t tend to fill the complaints after their first time.

Another interesting finding is related to the use of multiple channels by the same customers. As presented in Fig. 11, 95% of the customers (total 214) who sent complaints, called the call center as well. Furthermore, 78% (177) of them also sent werkmap messages. 74% (168) of customers who sent complaints, used both werkmap and questions (call center) as communication medium. 83% (13,740) of the customers who contacted through werkmap messages, also asked questions by calling the customer services. Total number of contacts related to the customers who preferred multiple channels are also described in Fig. 11. E.g. the customers who used both questions and werkmap messages, sent the 77% (51,178) of total werkmap messages (66,058).

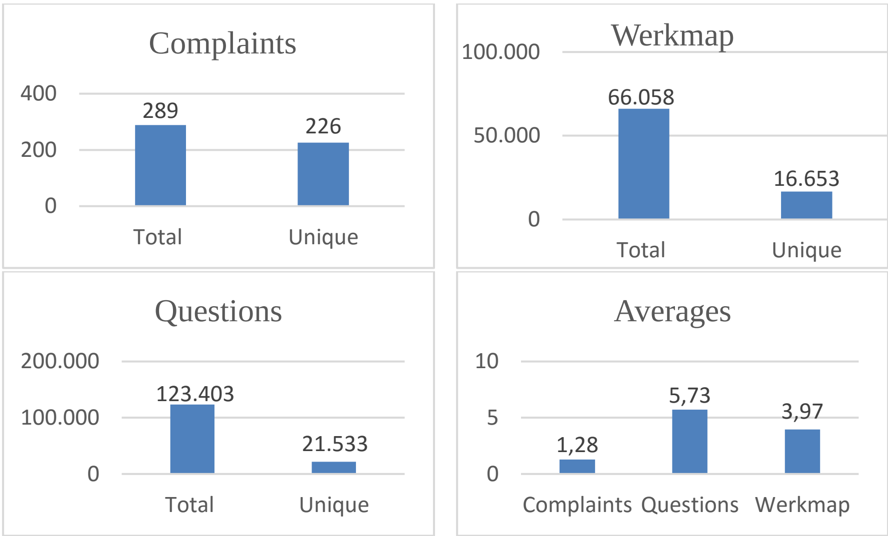

Fig. 9. Total number of communication channel uses. Second columns indicate the number of unique customers who contacted via complaints, werkmap and questions (call center)

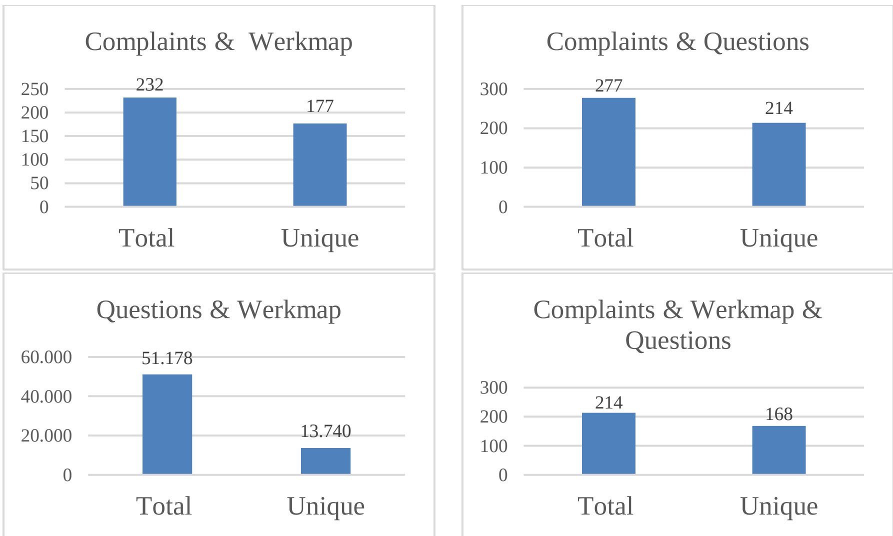

Fig. 10. Multiple use of communication channels by same customers.

To explore the statistics of click data of the relevant customers, we joined the tables comprising the information about various communication channels (complaints, werkmap and questions) with the click log file using the identification number of customers. The total amount of clicks in the provided original log data is equal to almost 7.2 million. The numbers of clicks by customers who sent questions, werkmap messages and complaints are 5.86 million, 5.57 million and 79.3 thousands respectively. The fact that the sum of individual clicks exceeds the total click logs, confirms again the finding discussed above which suggests that, majority of customers used multiple contact mediums.

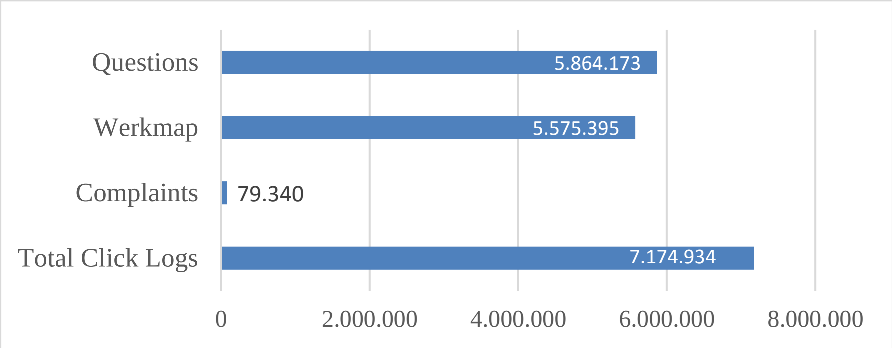

Fig. 11. Total number of click logs according to communication channels preferred by customers.

After joining the log data (clickstream) with the list of complaints, werkmap and questions (call center), we have also revealed that the related click data of some customers are not available. This finding implies that either these customers contacted through diverse communication channels mentioned above without surfing in the website or the click log data file misses the relevant data of these customers. Table 1 provides an overview to the statistics of these customers, suggesting that the click logs for 768 customers are not available.

Table 7. Total number of customers who contacted via diverse channels, extracted from Click Log Data and separate communication channel files (complaints, werkmap and questions).

Communication channels	# of customer in log data	# of customers in Communication channel files	Difference
Complaints	225	226	1
Werkmap	16,649	16,653	4
Questions	20,770	21,533	763
Total	26,647	27,415	768

6.2 Does the behavior of the customers change after they have send a Werkmap message, made a phone call or filed a complaint? What is the customer behavior on the site after customers have been in contact through the Werkmap or by phone?

To identify the trend (increasing or decreasing) in the usage of websites by customers after contacting UWV, the click data of customers have to be divided into "before and after" datasets describing the click before of customers after categorizing them in terms of used communication channel. However, generating such datasets is a complicated issue since the majority of customers contacted the UWV several times using the same communication medium (See Averages in Fig 10.). E.g. the issue is how identify the click behavior of a particular customer before sending a werkmap message, if he/she sent five werkmap messages in the given period.

To conduct such an analysis we propose an "overlapping intervals" approach. Consider we have *n* communication points of the particular channel by the same customer. The log data before the 1st communication point are considered as "before" data for all communication nodes. Likewise, the log data occurring after nth describe always the "after" behavior. According to the adopted approach, we consider the click logs between 1 and *n* as both "before" and "after" behavior corresponding to the position of the node in the given time interval. E.g. The click logs between the communication nodes 1 and *n* represent the "after" behavior for the node 1, which at the same time describe the "before" behavior for node *n*.

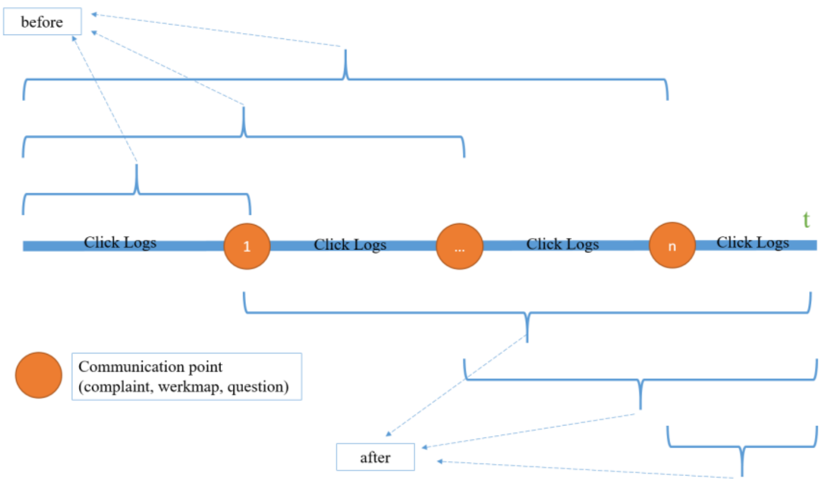

Fig. 12. The approach to identify the click logs before and after communication point.

Following this approach, we have identified the trend of using website after sending werkmap messages, questions or complaints. As Fig.14 suggests, the number of clicks have declined significantly after the customers sent the complaints and werkmap messages. This reduction rate is 34.09% for customers who sent complaints and 30.35% for customers who sent werkmap messages. The trend for using the UWV website after calling the call centers follows an opposite pattern. After asking questions, the use of website increased by 12.85%.

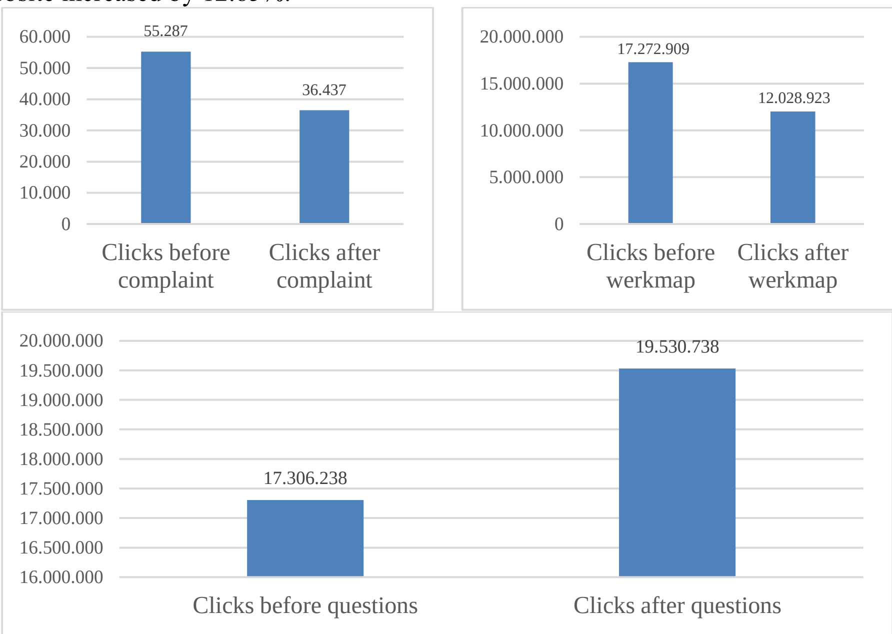

Fig. 13. The number of clicks after sending complaints, werkmap and questions

7 Challenge 5: Customer Behavior that Leads to Complaints

Within this section, we give an answer to the question: *Is there any specific customer behavior that directly leads to complaints?* This question is important to get insight into the logged data to further improve the application. Regarding that, the processing of complaints for the support-team of the website is very cost intensive, the complaints should be avoided. Therefore, the usage behavior analysis of the customers is very important for avoiding wrong usage behavior within the website. To extract and analyze these usage patterns we establish a three-step approach of analyzing the data. For this question, we need *dataset 1* and *dataset 5* ("complaints"). To analyze the behavior we extract certain usage patterns regarding Question 1. We use the following three-step approach.

Step 1: Join dataset 2 and dataset 5. First, dataset 2 and 5 were joined to only obtain user interaction data from customers which eventually filed a complaint. In order to separate the customer interactions before those very customers sent a complaint from the one that took place after they sent a complaint, the data was split into two segments (*before_complaint* and *after_complaint*).

Step 2: Clustering of segments. Using ProM, we then clustered the segments with the build-in sequence clustering algorithm in order to reduce the model complexity [7]. These clusters contain similar sequences (corresponding to similar usage behavior), which are more suitable for deriving usage patterns compared to considering the entire segment. Table 8 describes cluster statistics.

Table 8. Final clusters resulting from sequence clustering algorithm.

Cluster	Cases	Events
#1	710	5354
#2	519	6994
#3	402	5748
#4	511	6918
#5	646	5449
#6	625	5861

The clustering of the log data will give us an aggregation of similar usage behavior regarded the click-stream, which represents a sequence within the particular cases. The single sequences in the log data have a strict analogy to actually usage behavior of the users with the software system. Therefore, this clustering mechanism gives us the main patterns of users, who sent a complaint. To analyze the click behavior in the next step, we use the discovery mechanism of Disco to derive the relevant usage patterns.

Step 3: Derivation of usage patterns. For the derivation of the usage patterns, which lead strictly to a complaint, we load the clustered log data into the Disco software. The following usage patterns are described regarding a high relative frequency to ensure the detection of general problems of certain users with the software system and not particular cases or users. For the identification of possible user problems with the system, we focus on the duration of site usage of the users. Therefore, the metric mean duration as well as the absolute frequency and the max duration are very useful to identify problems and anomalies within the system. The following process models or extractions of the mined process models show problems or bottlenecks concerning the system usage for the first cluster. The pattern introduced in Fig. 15 shows that *mijn_sollicitaties* (dutch for *my applications*) has a direct connection to the website *contact*. As mentioned in the graph, the mean duration of the site *mjin_sollicitaties* is 23.3 minutes which is too long to check own application.

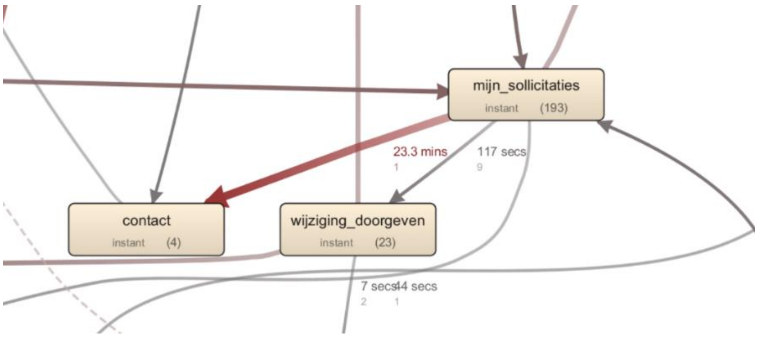

Fig. 14. Extract of cluster #1.

Therefore, it could be reasonable to prove some user specific information e.g. for the guidance of the website. In order to the results of question one we have been recognized that the normal usage behavior of the customers is that the click after about 22.7 seconds to the next page *wijziging_doorgeven* (dutch for *forward changes*). Therefore, it could be promising to determine the reasons for this complaint, whether it is a general problem with the usability of this special website or the user have other problems. On a more aggregated level regarding with the most frequent activities, we visualized in Figure 16 the derivation of a more general pattern, which leads to complaints. The pattern shows that there is a long visit of the website taken. A reason for the long duration of this particular site could be the amount of open task of the page. The website should be further developed to improve this average time regarding user specific assistance systems like chats to get answers or support directly by the executed tasks. There are certain iterations on the *taken* (dutch for *task*) website. Another aspect is the general average duration time of the site taken before the users switch to the *home*-site. After they fulfill their task, the general way is to navigate back of the *home*-site and leave after they navigate to *werkmap* and to the site *mijn_berichten.*

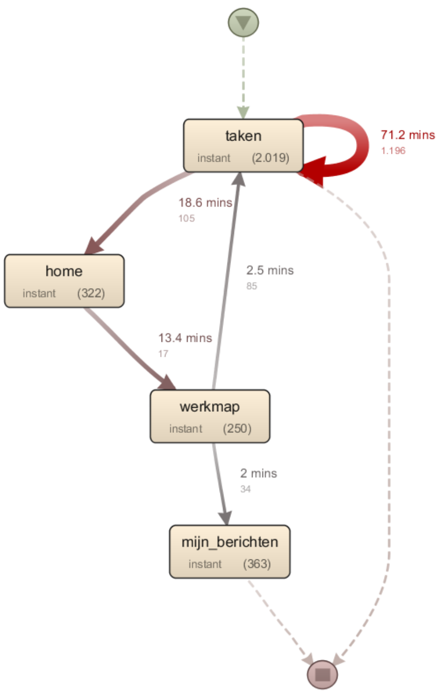

Fig. 15. Usage pattern of cluster #1.

The following extracts of the mined process models show some of the problems or bottlenecks concerning the system usage for the second cluster.

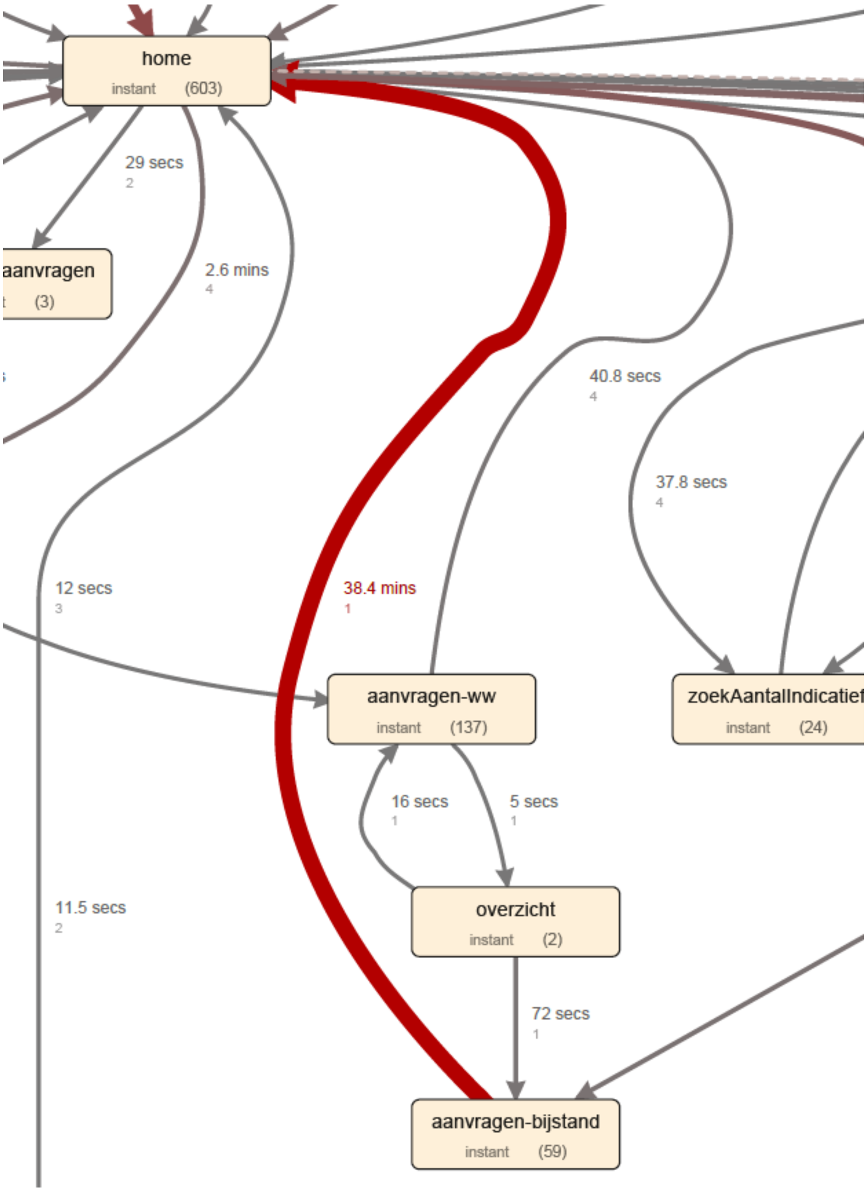

Fig. 16. Extract of cluster #2.

The pattern in Fig. 16 shows that *aanvragen_bijstand* (dutch for *requesting for assistance*) has a direct connection to *home*. As mentioned in the graph the mean duration of the site *aanvragen_bijstand* is 38.4 minutes, which is very long regarding the other site durations. Therefore, it could be reasonable to prove this site in detail to ensure a user specific guidance for processing the tasks on this site. Another reason for the long duration time could be a bad usability of this particular site. Therefore, it could be promising to determine the reasons for this complaint, whether it is a general problem with the usability of this special website or the user have other problems. There are more usage patterns which have in our opinion regarding the duration time a normal usage behavior. Nevertheless, they lead to a complaint. A Set of further usage patterns in an aggregated way is given in the following figures.

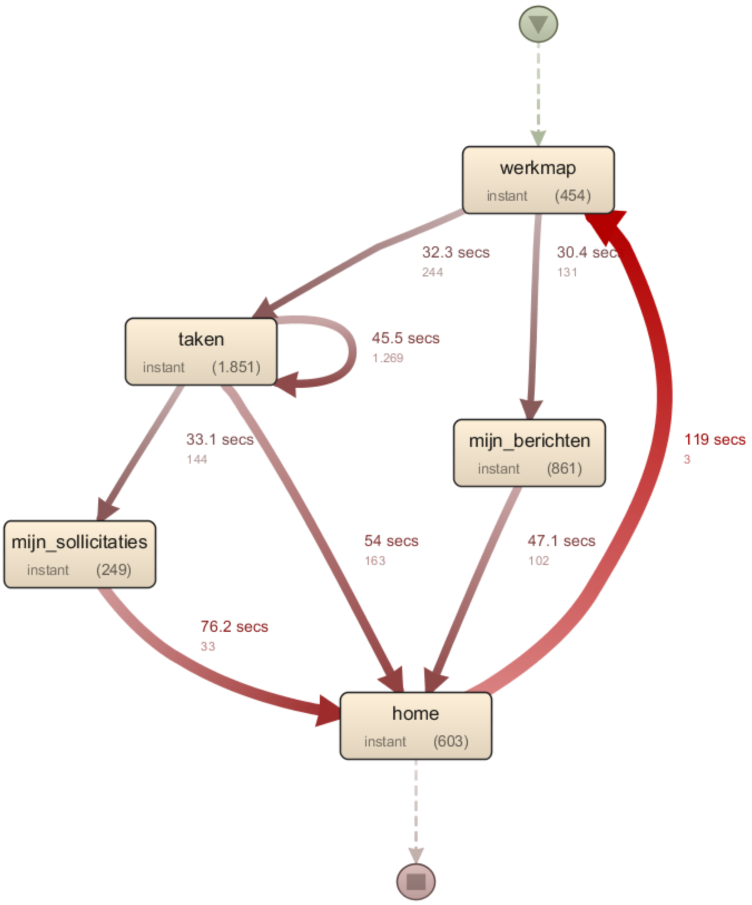

Fig. 17. Aggregated usage pattern for cluster two.

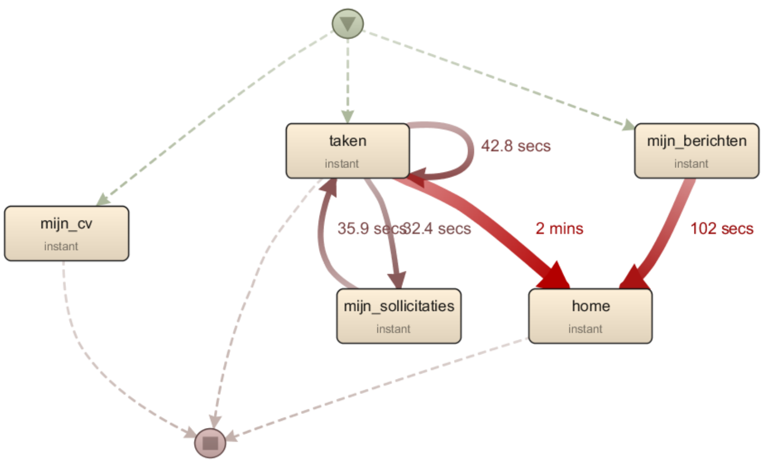

Fig. 18. Aggregated usage pattern for cluster three.

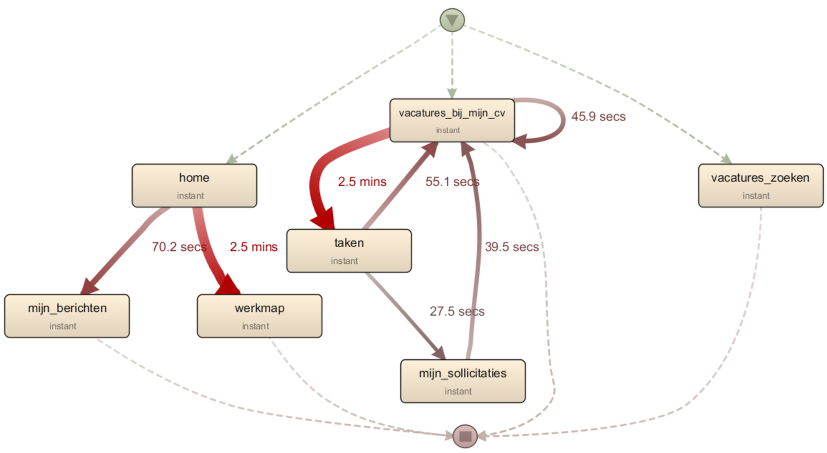

Fig. 19. Aggregated usage pattern for cluster four.

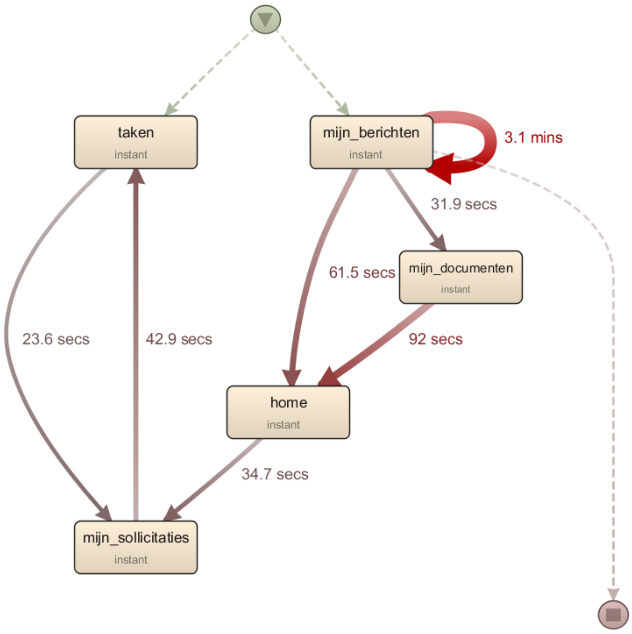

Fig. 20. Aggregated usage pattern for cluster five.

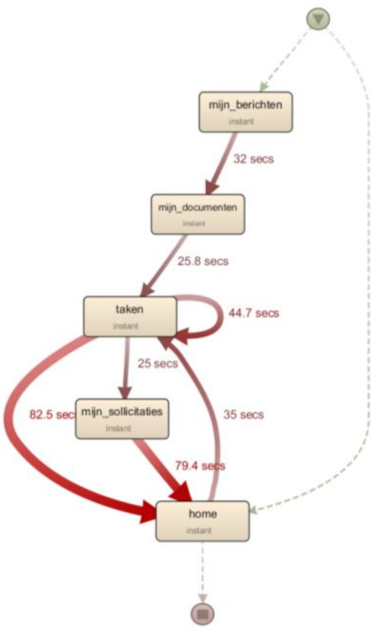

Fig. 21. Aggregated usage pattern for cluster six.

8 Conclusion

In our study, we have investigated the usage patterns of UWV (Dutch Employee Insurance Agency) website by customers and examined underlying process models. The click log data extracted from the usage of UWV website and the information about the communication channels used by customers such as complaints, werkmap and questions (call center) were used as inputs for the underlying analysis. After providing a detailed introduction and a brief overview to the tools used for analysis, we have structured the rest of the underlying paper by answering each question defined within the frame of BPI Challenge.

In this paper we have addressed not only the identification of diverse usage patterns considering various aspects such as demographic characteristics of customers, but also examined the causes, directions and effects of the change trends over time in the usage of website. Additionally, the process models were extracted using the log data which provide a detailed overview to the transition paths among business processes in the context of website usage. Our findings reveal that both the number of website usage by existing visitors and the number of click logs per session decreases over time. The detail of this analysis have important broader implications for future interventions in order to prevent the undesired situations. We have also determined various issues related to the usage of websites such as cycles between two processes, significant decrease in the relative frequency of particular websites, crucial variability in different age categories which may provide hints for the future development and maintenance of the website specific processes. Such findings related both to usage patterns and process models serve as an invaluable basis for identification of bottlenecks in the business processes and detecting the deviations from designed path. Furthermore, we applied deep learning algorithm with the goal to identify the future business process events (transition to the other website in our case) in runtime.

We have also researched the transition of customers to more expensive channels such as sending complaints, werkmap messages and asking questions which are undesired by the UWV due to high support costs. The findings reveal that the customers tend to use the same communication channels repeatedly. The majority of them also use the multiple channels. The results of analysis also suggest that the usage behavior of the websites before and after contacting the service team through expensive communication channel differ significantly. The customers tend not to use the website after contacting via werkmap and complaints. However, this trend is opposite after they contact call centers. Furthermore, we have examined the specific behavior patterns which may lead to filling complaints. After clustering the relevant log data we have identified several possible reasons for such problems. E.g. spending long time with the assistance function of the website directly before sending complaints can be linked with the lacking usability.

We are strongly convinced the use various novel process mining techniques will help to improve the service of UWV by identifying the reasons of shortcomings. Moreover, we would like to express our gratitude and appreciations to UWV for providing these invaluable datasets and BPI committee for organizing this event.

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