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Masterarbeit

Understanding and Predicting Web Browsing Behavior

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Aufgabenstellung

Understanding and Predicting User Browsing Behavior

Problem Statement To be added

Scope of the Thesis To be added

Tasks (1) Conduct a literature review to identify research questions regarding clickstream research that are of interest to researchers and practitioners
(2) Design a machine learning based model in clickstream modeling and creating an appropriate experiment with theoretical support to justify model performance and its interpretability
(3) Develop an web application as a demonstration of the model and evolving it as a generic architecture for the proposed model.

Requirements Strong skills in mathematical modeling and machine learning approaches, independent scientific work and creative problem solving, industrial experience in web development and architecting.

Keywords Clickstream, User Browsing Behavior, Machine Learning, Web

Ich erkläre hiermit, dass ich die vorliegende Arbeit selbstständig angefertigt, alle Zitate als solche kenntlich gemacht sowie alle benutzten Quellen und Hilfsmittel angegeben habe.

München, February 6, 2019 . . . .

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Abstract

Clickstream applications appeared at the end of last century and have proliferated the heart of our Internet world. Trades, public opinions, and almost every trace of web requests are precisely recorded on server-side log files. The fundamental interaction between a web service client and server stands immutably, despite the fact that mobile devices have governed our daily life. In this thesis, we propose a machine learning model that characterizes user browsing behavior while involving multi-tab branching and backtrack actions in a browser instead of web request-based clickstreams. We call it the Action Path model. To justify our model, we first established a lab study and collected individuals' clickstream data, which consisted of chronologic URLs and corresponding stay durations of each URL with designed nine different contexts given web browsing tasks for three mainstream websites based on the theory of information behavior. Each website has three types of tasks, including a goal-oriented task, fuzzy task and exploring browsing task. They characterize the corresponding three browsing behaviors. By analyzing the subject's trace from our lab study, we seek to archive the following goals: 1) Understanding: identify if browsing behaviors are distinguishable and finding common patterns that appear in an action path. 2) Classification: to separate and report browsing behaviors on the web, which help users better understanding their status. 3) Prediction: present the future click path more than one step with the given context of the browsing history in a session. To achieve these goals, our quantitative analysis indicates that goal-oriented, fuzzy and exploring browsing behaviors are classifiable with 100.00% precision based on the combination of chronologic URLs and stay duration. The prediction performance of our model shows higher than 60% accuracy for 3 to 5 steps of future clickstream prediction. Meanwhile, our qualitative analysis of the clickstream indicates 5 observed patterns, including "ring","star", "overlap", "hesitation" and "cluster" patterns, which represent the patterns of an action path. As an illustration of application, we also developed a browser plugin that proactively serves users, as well as suggesting predictions of the possible future user clicks. Furthermore, a generalized design of our model and plugin communication protocol are discussed for possibility of formalizing them as standard Web APIs to help designer and developers to improve and monitor the user experience of their products. To the best of our knowledge, this is the first such detailed study regarding web browsing behavior modeling based on client-side collected clickstreams.

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1 Introduction

> That men do not learn very much from the lessons of history is the most important of all the lessons that history has to teach.
>
> Aldous Huxley

1.1 History of Clickstream Research

The word “clickstream” [Friedman, Wayne and Weaver, Jane, 1995] was first coined in 1995, a media comments article introduced a novel concept of tracing cyberlife of users over the nowadays “Internet”. Informally, a “clickstream” contains a sequence of hyperlinks clicked by a website user over time. At the same year, the most popular server software Apache HTTP [The Apache Software Foundation, 1995] proxy on the Web was developed with a feature that records access log of entries. Afterwards, people realized the potential danger and value of tracing cyberspace, which a large discussion of clickstream influences, such as frequency based mining of clickstream [Brodwin, D., D. O’Connell, and M. Valdmanis., 1995], privacy concerns [Reidenberg, 1996], and database schema of session based time series data [Courtheoux, 2000].

Privacy discussion concludes collecting traces over net clearly offence the rights of users, the practice violates the openness and transparency of a service to a user. Serious criticism arise the tracing becomes a loss of democratic governance [Gindin, 1997].

Technologies is not guilty. After years of discussion, positive opinion proposes the rules [Reidenberg, 1996] and regulations [Skok, 1999] in cyberspace, means of protecting information privacy in cyberspace transactions [Kang, 1997], and approaches to resolve conflicting international data privacy [Reidenberg, 1999].

Meanwhile, bussinessman agilely responses to the concept and immediately initiate commercial tracking of their customer to improving marketing affects [Novick, Bob, 1995], customer service and precise advertisement [Reagle and Cranor, 1999, Bucklin and Sismeiro, 2000], even measuring product success [Schonberg et al., 2000].

At the turn of this century, common reviews start accept the technology of clickstream, clickstream data has confirmed by industrial practice, which opens a new era in customer service [Walsh, John and Godfrey, Sue, 2000], most of website users start accept their click path data be aggregate analysed on the server side [Carr, 2000].

Clickstream data grows fast and becomes plentiful, researchers start convey the original concept of clickstream, tracking customer selections, into various applications, such as usability testing [Waterson et al., 2002a], understanding social network sentiment [Schneider et al., 2009], and developed visualizing technique to better interpret clickstream data [Waterson et al., 2002b].

Analysis, reports and characterizing of clickstream gains its popularity, Mobasher et al. [Mobasher et al., 2001] suggests personalize user based on association rule from their web usage data. Chatterjee et al. [Chatterjee, Patrali and Hoffman, Donna L and Novak, Thomas P, 2003] first proposed E-commerce websites should use clickstream to tracking customer navigation pattern instead of essential choice, associating and binding products for observing responses of a customer.

With the arise of characterizing and behavior understanding on clickstream data, more and more research proposes methods for the understanding of given server clickstream data. Padmanabhan et al. [Padmanabhan et al., 2001] proposed an algorithm to address personalization from incomplete clickstream data, which implies a security problem potential information leak from clickstream data. Moreover, affected by search engine indexing, Lourenco at al. [Lourenço and

Belo, 2006] recommends an approach for the detection and containment of web crawler based on server side recorded visiting log file.

After a short review of clickstream history, almost all research put forward their methodology based on server recorded clickstream data. Note that a daily user is always allowed accesses parallel pages and windows simultaneously, even allow switching across multiple websites for a browsing purpose. An obvious missing aspect of those papers is the server recorded data tend to incomplete for characterizing a visited user, and the log data can only applied on a specific website. As an observation, our research no longer serves server side clickstream, but focus and contributes to a client side collected clickstream data for a real visiting session of a user in a browser.

1.2 This Thesis

The main part of the thesis is structured in different chapters, and answers the following three research question groups:

1. **Understanding**: Why collecting clickstream on client-side differs from server-side collecting? What are the most significant, identifiable user behaviors and activity patterns can be observed or algorithmically detected in the context of web browsing that indicates information needs, and in which form of quantitative data can characterize a definitive boundary to distinguish browsing behaviors of a user?

2. **Classification**: How accurate or how affirmative we can model or identify the proposed browsing behaviors progressively that makes an intelligent system serves proactively?

3. **Prediction**: How much future movements of a user can be accurately inferred from the context of web browsing, and how much context is required for the prediction?

Chapter 2 discusses the existing user behavior research based on clickstream data firstly. Then discussed the evolution of theory regarding information seeking behavior as our experiment foundation. In addition, we summarized the reason of recent raise of neural approach in different scientific area and the state-of-the-art direction for sequence learning, whose proposed in neural network research. Chapter 3 defined the completion efficiency of a clickstream first, then we formalizes our proposed sequence to sequence encoder and decoder models for client-side clickstream as well as the training techniques for the proposed model. In subsequent chapter, Chapter 4, we present our experiment for a lab study, and construe the design reason of context given web browsing tasks for our subjects based on information behavior theory. Afterwards, in Chapter 5, based on SVM, t-SNE and our proposed action path model, we conducted a quantitative analysis with described data from our lab study, the evaluation shows a very promising results. Moreover, we visualize the clickstream through directed graph, by combining our training model outputs, we also performs a qualitative analysis to all clickstreams, and the analysis gives evidences that further verified the correctness of our model. In Chapter 6, as a consequence of our analysis, we developed a browser plugin for Google Chrome as a possible application to our model. The plugin can fairly predict the next possible visiting pages of a user. In addition, we generalize the design of our plugin architecture between client and server, and then discuss the possibilities of being a standard web API to web developers.

In the last two chapters, we discuss our decisions made in the thesis and limitations of this work, summarize the findings of our thesis, as well as the possible future improvements and directions of the thesis in the final chapter.

2 Related Works

If I have seen further it is by
standing on the shoulders of Giants.

Isaac Newton

In this chapter, we discuss the former research that relates to our work, including the existing approaches to clickstream behavior modeling, the evolution of information behavior theory regarding how it adapts to our digital world, as well as the most related recent advances regarding sequence learning.

2.1 Clickstream Behavior Modeling

Clickstream behavior research can be traced back to the year when the word "clickstream" was invented. Early clickstream behavior research studied the navigational behavior of user [Mandese, 1995,Brodwin, D., D. O'Connell, and M. Valdmanis., 1995] and they binary classified clickstream based on the degree of linearity.

Mobasher et al. discovered the effective and scalable techniques [Mobasher et al., 2001] for Web personalization by using association rules and built a recommendation system. Goldfrab investigates [Goldfarb, 2002] the website choice behavior based on clickstream data and suggests that clickstream simulate company strategy changes. Afterwards, Chatterjee et al. [Chatterjee, Patrali and Hoffman, Donna L and Novak, Thomas P, 2003] first conduct the previous research regarding clickstream to an actual commercial website. They found that clickstream represents an implication that dynamic advertising based on customer clickstream history influence the future clickstream of the customer and increase the interaction with the dynamic advertisement. More technically, Ting et al. uses common sequences to find unexpected browsing behavior [Ting et al., 2005], and then use their findings to improve website design.

The most recent research evolved the approach of clickstream modeling, Wang et al. [Wang et al., 2016] proposed an unsupervised approach to model clickstream without labeling. Chi et al. proposed an analysis framework [Chi et al., 2017] for the general understanding of online information behavior in a specific page. However, their framework only fits for server side collected clickstream other than a real user clickstream.

Then, Wang et al. [Wang et al., 2017] improved their unsupervised approach, and summarized more comprehensive review to the existing approaches, such as common subsequences of clickstreams and graph clustering based classification for clickstream behavior modeling that identifies spam and abuse for a specific website. Park et al. models and detects a behavior change among student while learning based on Poisson process [Park et al., 2017] to help improve online learning experience. Amo et al. [Amo Filvá et al., 2018] further visualizes search-stream behavior that serves student clickstream data from a class, and Shimada et al. proves [Shimada et al., 2018] online change detection while monitoring on student behavior is possible based on a sliding window.

Zaloudek gives an review on the comparison [Zaloudek, 2018] traditional method to model clickstream data, then proposed a principle component analysis based method for a semi-supervised learning of clickstream data, however their approach does not work well on clustering task, and the best performance is obtained by traditional multilayer perceptron algorithm. Chandramohan and Ravindran then further investigate the neural approach on clickstream mining [N and Ravindran, 2018], they verified that complex LSTM with Attention mechanism is able to capture whether a user is intent to buy a product or not based on server side collected clickstream. Surprisingly, Gundala and Spezzano [Gundala and Spezzano, 2018] simply use a Lasso regression based on sophisticated feature engineering archived AOC score 0.769 for reader demand hyperlink prediction on Wikipedia clickstream dataset.

Kammenhuber et al. is the first study [Kammenhuber et al., 2006] regarding client side clickstream. They proposed a finite-state Markov model that models user's search behavior on a level of topic categories. Unfortunately their dataset are collected from network package traffic, and did not consider the time a user spend in each page.

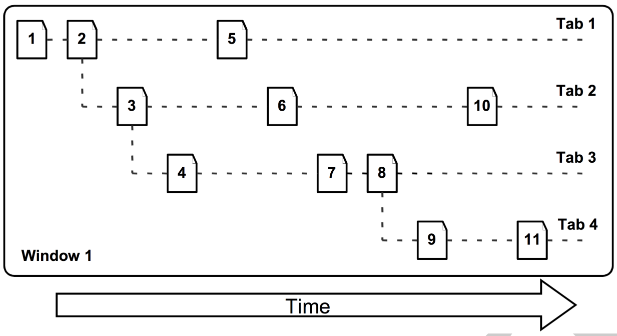


Figure 2.1: Parallel browsing behavior: branching phenomenon [Huang and White, 2010]

Liu et al. [Liu et al., 2010] studied a specific user behavior on dwell time on web pages, and concluded that Weibull distribution is the most appropriate distribution to characterize this behavior. Huang et al. [Huang and White, 2010, Huang et al., 2012] further noticed the behavior of branching parallel browsing and backtracking browsing behavior on modern browsers, as shown in Figure 2.1, and presented an frequent analysis for the distribution of these two behavior individually.

Unfortunately, as we discussed above, the existed research regarding clickstream behavior modeling are either server-side modeling for an individual website or individually modelized for client-side behaviors with limited information of clickstream, which does not stands for a ground truth of user behavior. Besides, the existed approaches are based on self-constructed features, the property of Markov memoryless and etc. Though the most recent approach use neural networks, their findings only applies to specific context. From the point of view of user behavior, they neither unambiguously justifies the foundation of their model, nor providing a large performance improvement of their model.

We, in this thesis, serialize the client side chronologic URL sequences with combines all these individually studied phenomena including the branching and backtracking browser feature. With this chronologic URLs, we seek to understand and model the essential user behaviors patterns while browsing on the Web.

2.2 Sequence to Sequence Learning

Sequence learning is a large scope of research and has been applied to many fields such as typical application machine translation in nature language processing.

Recurrent Neural Network (RNN) was describe by Werbos [Werbos, 1990] and Rumelhart et al. [Rumelhart et al., 1988], the original RNN generalize feedforward neural network for sequence based data.

Given a sequence of input $(i_1, i_2, ..., i_T)$, the original RNN computes a sequence of outputs $(o_1, o_2, ..., o_T)$ by iterating the activation function Equation 1:

$$o_t = W_{oh}\sigma\left(W_{hi}i_t + W_{hh}i_{t-1}\right), t = 1, 2, ..., T \tag{1}$$

where $\sigma(x) = \frac{1}{1+\exp\{-x\}}$, and W_{oh}, W_{hh}, W_{hi} are weight parameters between output, hidden and input layers.

The origin RNN simply use a linear weights and a σ non-linear transformation between inputs and outputs as a recurrent unit. The most widely used recurrent unit in RNN is the Long Short Term Memory (LSTM) unit [Hochreiter and Schmidhuber, 1997] or Gated Recurrent unit (GRU) [Cho et al., 2014], they provides a game-changing performance than traditional hidden Markov models in machine translation [Garg and Agarwal, 2019].

LSTM has a context cell and three regulators: Input gate, output gate and forget gate. The context cell keeps dependencies between inputs of the unit as long term memory. Input gate take historical hidden state and current input and controls the input value to the recurrent unit, output gate responsible for the control of output activations, and forget gate resets and decides retaining values of the recurrent unit as a short term memory. Similarly in GRU, it simplifies the structure of LSTM into a update gate and a reset gate.

On the other hand, the vanilla RNN transfers and maps a sequence to another sequence if and only if the inputs and the outputs are aligned with equal length. Apparently, the major constraints of the vanilla RNN is the model cannot address a problem if inputs and outputs provided in different length with complicated and non-monotonic relationships.

Stutskever et al. [Sutskever et al., 2014] present a general end-to-end approach to sequence learning model in machine translation that estimates the conditional probability of $p(o_1, o_2, ..., o_{T'} | i_1, i_2, ..., i_T)$ where $(i_1, i_2, ..., i_T)$ is an input sequence, $(o_1, o_2, ..., o_{T'})$ is a corresponding output sequence, and T is not required to be equal with T'.

In machine translation, a series of words are considered as a sequence of vectors, neural network based models considered representation learning of nature languages. The initial vectors of word were one-hot encoded vectors and get updated over training and learning.

The recent advances of representation learning uses a distributed representation of word2vec model [Mikolov et al., 2013a], which achieve better performance in natural language processing. The word2vec model introduced continuous bag-of-word and skip-gram model as an efficient method for learning high-quality vector representation of words, and bag-of-word is faster while skip-gram is slower but get better performance for infrequent words.

2.3 Theory of Information Behavior on the Web

The thesis relates to information behavior theory since it supports the foundation of our user study. This subsection discusses how the theory was concluded and the principles of the theory that sustain our thesis.

Information behavior research encompasses intentional information seeking and unintentional information encounters, and the roots to information behavior theory relates to information needs and uses [Fisher and Julien, 2009] that arose in the 1960s.

However, the concept of information seeking behavior, was coined in late 1981 by Thomas Wilson [Wilson, 1981], and he tries to formalize the process or activities of a conscious effort while information needs and uses. Figure 2.2 illustrate the model of information behavior was proposed.

Wilson's model has been involved many years since its origin, and it was revised and adapted to our digital world since the digital systems learns user preferences and changes [Giannini, 1998] the way we receiving information.

David Ellis described a detailed group of activities for information seeking behavior [Ellis, 1989], and then applied in physical and social science [Ellis et al., 1993] and industrial environment [Ellis and Haugan, 1997]. In addition, his analysis was based on grounded theory approach [Aceto et al., 1994] and semi-structured interviews.

Afterwards, Choo et al. adapts Ellis' Model and discussed [Choo et al., 1999] the information seeking behavior on the web through different activities rather than a single process, the applied activities are: starting, chaining, browsing, differentiating, monitoring, and extracting.

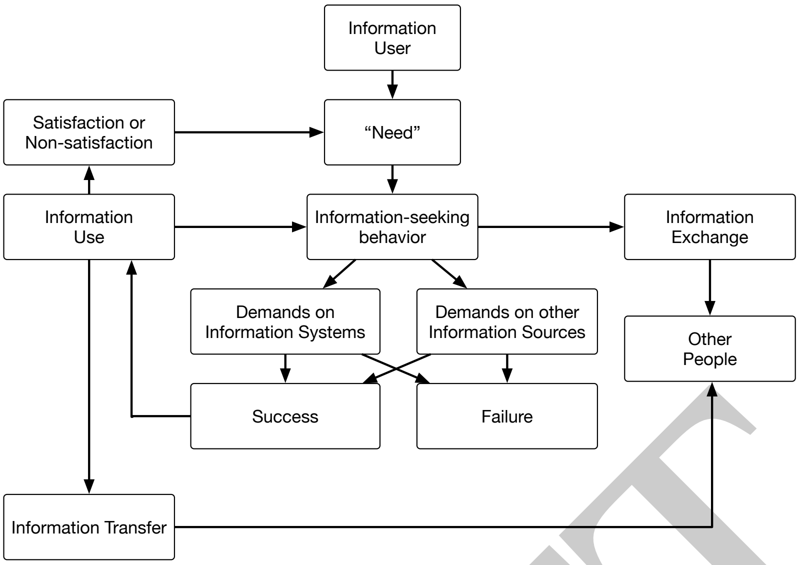

Information User
"Need"
Satisfaction or Non-satisfaction
Information Use
Information-seeking behavior
Information Exchange
Demands on Information Systems
Demands on other Information Sources
Other People
Success
Failure
Information Transfer

Figure 2.2: Wilson's information seeking behavior model [Wilson, 1981]

"*Starting*" on the web indicates that a user identifies websites or pages that containing the information of interests. "*Chaining*" indicates that a user follows on starting page to other related pages. "*Browsing*" then represents the activity that a user only skimming on the web and quickly viewing the top-level informations. The "*differentiating*" describes that a user on the web is selecting useful pages and choosing differentiated. "*Monitoring*" activity is used for receiving updates on the sites, or revisit the previously visited pages. Finally "*extracting*" is the activity that a user systematically extracts informations from a interested page or website.

By applying these activities, Choo et al concludes general user behaviors on the web are undirected viewing, conditioned viewing, informal search and formal search. Johnson further describes [Johnson, Ross, 2017] seven more detailed behaviors patterns on the web, but did not given a working study that verify or prove their formation.

Although Wilson's model and Ellis' model are revised in recent works, however these improvements are more generic and too complex for describing user information behavior on the web, which cannot adapts to our experiment design (discuss detailly in Chapter 4 and Section 7.2). In this thesis, we only uses the an antecessor of Wilson's framework [Wilson, 1997] and Ellis' model [Ellis and Haugan, 1997] to formalize and justify our lab study experiment later in Chapter 4, as a foundation of our work.

3 Action Path Models

> It is impossible to separate a cube into two cubes, or a fourth power into two fourth powers, or in general, any power higher than the second, into two like powers. I have discovered a truly marvelous proof of this, which this margin is too narrow to contain.
>
> Pierre de Fermat

In this chapter, we formalize few concepts and metrics in clickstream data, and then describe a proposed clickstream model named *Action Path model* based on a recurrent neural network that models a client-side web browsing behavior. An *action path* is different than the original clickstream concept since a user may *switch browser tabs* for parallel viewing [Huang and White, 2010] or uses *back button* for backtracking viewing [Huang et al., 2012] as we discussed in Chapter 2, namely, a user performes a visit action. A server-side collected clickstream does not contain such detailed level of user clickstream. The term *action path* is a generalized concept of clickstream, which replaces individual URLs to chronological ordered user actions (with back button and browser tab switch effects) in a browser. Figure 3.1 illustrates a simplified version of an action path that compares vanilla clickstream.

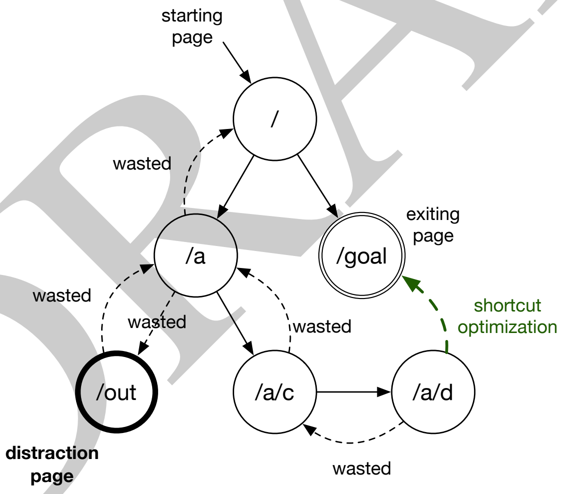


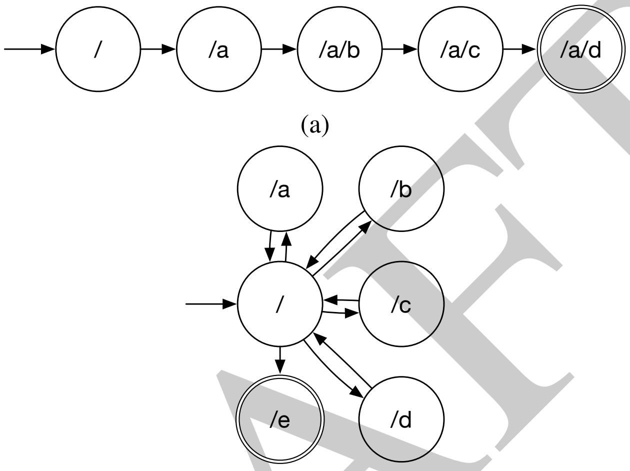
Figure 3.1: A simple action path. A user starts from the starting page, and performed a series of page click actions, ends on a exiting page. The server side records clickstream in the following order: / → /a → /out → /a/c → /a/d → /goal. However the actual user actions are: / → /a → /out → /a → /a/c → /a/d → /a/c → /a → / → /goal. The records from server side lost the interaction details between users and browsers. Node that /out is a distraction page in the graph, which may located in a different website (e.g. advertisement), and black dashed arrorws are wasted user actions. The /goal page may not clear in the beginning of the clickstream, one can generate a shortcut optimization navigation to the /goal page while more clickstream context be presented, i.e. an optimized user action is / → /a → /a/c → /a/d → /goal. In this case, the demand page of the visit session is discovered in /a/d.

For the convenience of discussion, **we indiscriminate the use of term *action path* and *clickstream* in this thesis to indicate a chronologically ordered user actions**.

3.1 Completion Effeciency

An action path of a visiting session starts from a starting page and ends on an existing page. Since we consider the effect of browser back button and browser tab switches, a previous page could easily be visited twice, if a user clicked the back button. Therefore, a page may direct to multiple pages. *For instance, an action path can degrade to a linked list if the user clicks through different pages without using the back button and switching tabs; or an action path can become a 1-to-n bipartite graph if a user use back button back to the previous page after clicking a page or only switching tabs from a specific page to one another*, as shown in Figure 3.2.

As a result, we define a term *completion effeciency* based on shortest path from starting page to exiting page, and stay duration of the action path.



(a)

(b)

Figure 3.2: Two particular case of an action path: an action path that degrade to a linked list if the user click through different pages without using back button and switching tabs (3.2a), and an action path that represented in 1-to-n bipartite graph if a user use back button back to the previous page after clicking a page or only switching tabs from a specific page to one another (3.2b).

Let a directed cyclic graph represents an action path, each node represents a visited page, and each edge has a weight that represents the study duration of its tail node. Assume the total stay duration of the shortest path from the starting page to the existing page is d_s, and the total stay duration of the action path is D, the number of nodes in the shortest path is n_s, the total nodes in an action path is N, we define the *completion efficiency E* is as follows Equation 2:

$$\begin{gathered} E = w_1 \frac{n_s}{N} + w_2 \frac{d_s}{D} \\ w_1 + w_2 = 1 \end{gathered} \tag{2}$$

where w_1, w_2 are hyperparameters to balancing the importance of action path and stay duration. According to the discussion of two special cases of action path, it is trivial to show the range of E is $(0,1]$. As a compliment, we define *zero completion efficiency* if and only if a user cannot complete a clickstream in a browsing session. Therefore we have a range of E is $[0,1]$.

Remark 1 The definition of completion efficiently uses the term of shortest path, which is the problem of finding a path between the starting page and exiting page in an action path (directed cyclic graph) such that the sum of the stay duration of its constituent pages in minimized. The problem can be solved by Dijkstra's [Dijkstra, 1959] shortest-path algorithm. It selects the unvisited nodes with the smallest weights, calculates the distance through it to each unvisited neighbor, then updates the distance of neighbor distance if the distance is smaller than one another. The process converges to the shortest path.

Remark 2 An action path may increases with more nodes (web pages) over time. The starting page of an active path was always the first page when the browser was opened. However, one can always treat the currently visited page is the exiting page due to we do not know when a user will exit browsing overtime at the moment. Consequently, function E is changing over browsing.

Remark 3 We use completion efficiency as a feature for a classification task in Section 5.2.1.

3.2 *url2vec* Embedding

As we discussed in Section 2.2, we convey similar idea from word2vec model and propose our *url2vec* model for client side clickstream data.

The purpose of url2vec model is to construct URL representations that better predict the surrounding URLs in a clickstream. Briefly, given a clickstream of urls $\mathrm{URL}_1, \mathrm{URL}_2, ..., \mathrm{URL}_T$, the objective of url2vec is to maximize the average log softmax probability:

$$\begin{aligned} &\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq i\leq c, i\neq 0}\log p(\mathrm{URL}_{t+i}|\mathrm{URL}_t) \\ p(\mathrm{URL}_{t+i}|\mathrm{URL}_t) = &\frac{\exp\left(v_{\mathrm{URL}_{t+i}}^{\top} v_{\mathrm{URL}_t}\right)}{\sum_{\text{all URLs}}\exp\left(v_{\mathrm{URL}_{t+i}}^{\top} v_{\mathrm{URL}_t}\right)} \end{aligned} \tag{3}$$

where c is the size of embedding context, which is a function of starting page, v_{URL_t} is one-hot encoded representation of input URLs, and $v_{\mathrm{URL}_{t+i}}$ is the vector embedding of output representations.

Remark 1 The model described by Equation 3 is essentially a three layer neural network: input layer of *one-hot* encoded URLs (a group of binaries that a component of a one-hot encoded vector is a representative of a URL under a finite set of existing URLs), a hidden layer of feature representation and an output layer share weights to the learned embeddings of input URLs.

Remark 2 The probability in Equation 3 is impractical due to $\nabla \log p(\mathrm{URL}_{t+i}|\mathrm{URL}_t)$ is large because of exponential terms in softmax, two numerical optimizations [Mikolov et al., 2013b] based on Hofmann Tree and Negative Sampling are proposed by Mikolv.

Remark 3 The probability can also be interpreted from a Bayesian perspective, which provides an intuition of this definition. $p(\mathrm{URL}_{t+i}|\mathrm{URL}_t)$ can be considered as a posterior probability. Since v_{URL_t} was initialized as a one-hot encoded vector input to the embedding neural network, the item can be treated as a prior, and the denominator is a normalization term. Furthermore, the dot product between $v_{\mathrm{URL}_{t+i}}^{\top}$ and v_{URL_t} is a representation of consine similarity, which represents the closest surrounding URLs in same direction of vectors.

3.3 Action Path Model

Our model convey a similar idea from Stutskever's sequence to sequence translation as we discussed in Section 2.2.

An *action path* from user i in session j consist of a sequence of *url2vec* embedded vectors $(U_1^{ij}, U_2^{ij}, ..., U_n^{ij})$ and a sequence of time duration $(d_1^{ij}, d_2^{ij}, ..., d_n^{ij})$, since each URL has a corresponding number that represents the time duration of a user spent on a given page. Our action path

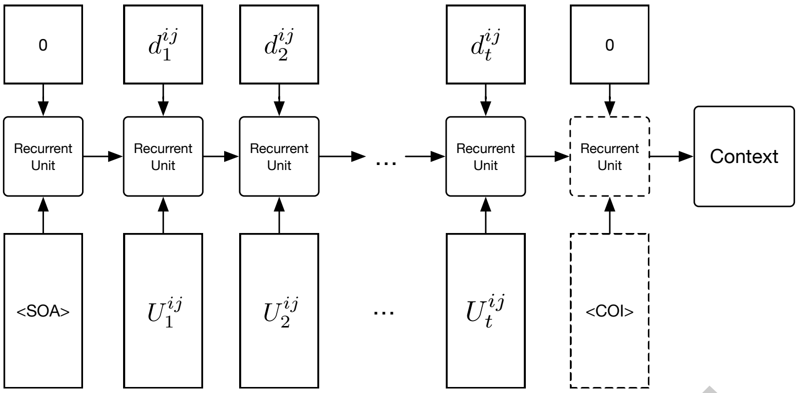


Figure 3.3: An unrolled illustration of context encoder of Action Path Model. In the encoder, a starting mark "<SOA>" is used as a sign of start feeding URLs, and a trigger mark "<COI>" as a sign to trigger decoder to decodes encoded context tensor. The trigger mark is automatically inserted after the k-th URL while training at the end of the encoder model over time, k is increasing over time. Besides, the recurrent unit is not detailly described in the figure but afterward.

model consist a context encoder and a context decoder that illustrated in the subsequent subsections.

3.3.1 Context Encoder

Context encoder encodes URLs one by one over timestamp and produces a context tensor that encodes the historical user actions, as shown in Figure 3.3.

In the encoder, we practically insert a starting mark (a mark is a special URL vector that differ from any other realistic URL one-hot encoded vectors) "<SOA>" (*Start of Action*) as a sign of start feeding URLs to the encoder, and a trigger mark "<COI>" (*Change of Intention*) as a sign to trigger decoder to decodes encoded context tensor.

Note that the input URLs to encoder's recurrent unit are preprocessed through url2vec embeddings, which has learned and updated from one-hot encoded vectors to densely distributed vectors.

3.3.2 Context Decoder

Context decoder decodes the context tensor produced by the encoder into a series of URLs. We practically feed a prediction mark "<SOP>" (*Start of Prediction*) as a sign to initiate the decoding of encoded context. At the end of decoder, decoder produces an ending mark "<EOA>" (*End of Action*) that terminates the decoding process.

Note that the decoder model in the training phase and prediction phase is different. In the training phase, teacher forcing strategy [Williams and Zipser, 1989] is used, the strategy supplies observed user actions as inputs in the decoder. In the evaluation phase, the decoder uses the output from the recurrent unit as an input, shown through dashed lines in Figure 3.4.

In our model, a decoder outputs vectors first, and we have two strategies in translating vectors to URLs. The first strategy is to use an argmax function to select the component with maximum probability of a vector; we use this strategy for performance evaluation in Section 5.3. Another strategy is to select a series of URLs that gains the highest joint probability, we discuss and use this strategy for action path optimization in Section 3.4.

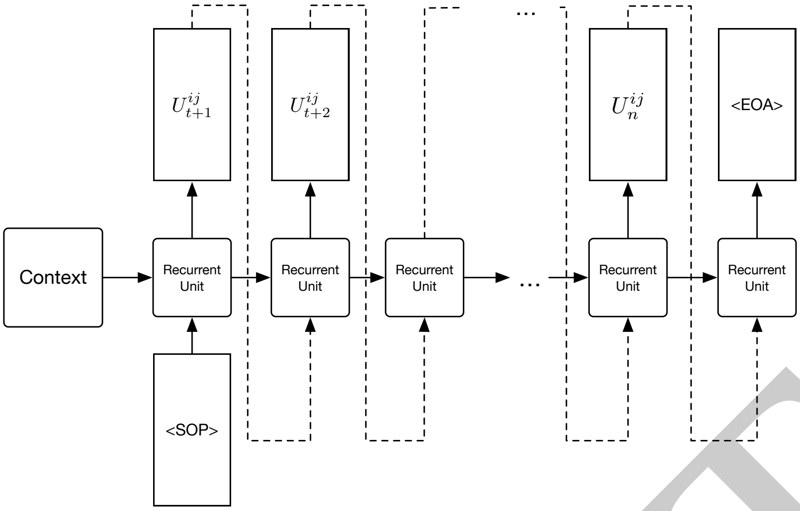


Figure 3.4: The context decoder of the Action Path Model. In the decoder, a prediction mark "<SOP>" is used to initiate the decoding process, and an ending mark "<EOA>" as a sign to terminate decode process. The output of the decoder uses a softmax intermediate operation to magnify and normalize the probability of predicted URL embedding. Also, the recurrent unit is not detailly described in the figure but afterward.

3.3.3 Recurrent Unit

The recurrent unit in the Action Path model is not as standard as original LSTM or GRU, which is one of the major contributions of the thesis. In our recurrent unit, when using LSTM as recurrent unit base, we also feed time duration $(d_1^{ij}, d_2^{ij}, ..., d_n^{ij})$ into input gate I_t, and others (forget gate F_t, output gate O_t, memory cell C_t and hidden state h_t) remains the same:

$$\begin{aligned} I_t =& \sigma(P^{(I)}U_t^{ij} + Q^{(I)}h_{t-1} + \frac{d_t^{ij}}{d_t^{ij}+1})) \\ F_t =& \sigma(P^{(F)}U_t^{ij} + Q^{(F)}h_{t-1} + b^{(F)}) \\ O_t =& \sigma(P^{(O)}U_t^{ij} + Q^{(O)}h_{t-1}) \\ C_t =& F^{(t)} \circ C_{t-1} + I_t \circ \tanh(P^{(C)}U_t^{ij} + Q^{(C)}h_{t-1}) \\ h_t =& O_t \circ \tanh(C_t) \end{aligned} \tag{4}$$

where $t = 1,2,...,n; P^{(I)}, Q^{(I)}, P^{(F)}, Q^{(F)}, P^{(O)}, Q^{(O)}$ are shared weight parameters, $b^{(F)}$ is a bias in forget gate F_t, $\circ$ represents element-wise product of two matrices.

When using GRU as recurrent unit base, we feed time duration $(d_1^{ij}, d_2^{ij}, ..., d_n^{ij})$ in to update gate Z_t, and others (reset gate R_t, hidden state h_t) stay the same:

$$\begin{aligned} Z_t =& \sigma(P^{(Z)}U_t^{ij} + Q^{(Z)}h_{t-1} + \frac{d_t^{ij}}{d_t^{ij}+1}) \\ R_t =& \sigma(P^{(R)}U_t^{ij} + Q^{(R)}h_{t-1}) \\ h_t =& (1-Z_t) \circ \tanh(P^{(H)}U_t^{ij} + Q^{(H)}h_{t-1}) + Z_t \circ h_{t-1} \end{aligned} \tag{5}$$

where $t = 1,2,...,n; P^{(Z)}, Q^{(Z)}, P^{(R)}, Q^{(R)}, P^{(H)}, Q^{(H)}$ are shared weight parameters, $\circ$ represents element-wise product of two matrices.

Remark 1 The units we described in this section is neither LSTM nor GRU since the input gate I_t or update gate Z_t introduces time duration d_t^{ij} as input, which is different from a simple constant bias in the first learnable bias in these gates. It is worth mentioning that adding bias to the gates are helpful to improve learning performance in LSTM [Jozefowicz et al., 2015], we also use the trick in our model as shown in F_t of Equation 4.

Remark 2 The term $\frac{d_t^{ij}}{d_t^{ij}+1}$ is a squashing mechanism, it normalizes d_t^{ij} from $(0,\infty)$ to $(0,1)$.

3.3.4 Ending Mark Interpretation

In context decoder, we mentioned an ending mark "<EOA>" that indicates the termination decoding process. However, the ending mark is different from other marks, since in practice, "<EOA>" is represented in different symbols of behavior-based categorical clickstream, which as a label to involve classification of user actions.

Assume action paths are labeled by one-hot encoded ending marks $\text{EOA}_1, \text{EOA}_2, ..., \text{EOA}_m$ and the last output of decoder hidden state is h_n, we have:

$$\begin{aligned} \hat{y} =& \text{argmax}(\text{softmax}(W^{(M)}h_n)) \\ \hat{y} \in& \{\text{EOA}_1, \text{EOA}_2, ..., \text{EOA}_m\} \end{aligned} \tag{6}$$

where $W^{(M)}$ is a weight parameter, and m is the number of ending mark categories.

3.4 Action Path Optimization

In traditional classification models, the arguments of the maxima (argmax) are used to select labels with the highest probability, scilicet, argmax selects predicted URLs with the highest probability of user action from decoder outputs. However, this method is under the condition of all outputs are independent in probability, which is not suitable for our action path optimization scenario.

In previous sections, our model feeds an input clickstream $(U_1^{ij}, U_2^{ij}, ..., U_t^{ij})$, and produce an output $(o_1, o_2, ..., o_m)$ that expect close to actual clickstream $(U_{t+1}^{ij}, U_{t+2}^{ij}, ..., U_n^{ij})$. Then the probability of expected clickstream is a conditional probability under the input clickstream. In other words, we need to solve an optimization problem:

$$\begin{aligned} &\underset{o}{\text{argmax}}\, p(o_1, o_2, ..., o_m | U_1^{ij}, U_2^{ij}, ..., U_t^{ij}) \\ =&\underset{o}{\text{argmax}} \prod_{k=1}^{m} p(o_k | U_1^{ij}, ..., U_t^{ij}, o_1, ..., o_{k-1}) \\ =&\underset{o}{\text{argmax}} \sum_{k=1}^{m} \log p(o_k | U_1^{ij}, ..., U_t^{ij}, o_1, ..., o_{k-1}) \end{aligned} \tag{7}$$

A heuristic approach can solve the optimization problem efficiently, namely beam search [Graves, 2012]. In each step of decoder output, we reserve the top-k best combinations of URLs and eliminate the rest of URLs from evaluation, and finally selects k best clickstreams. The pseudocode is given that adapts vanilla beam search to URL prediction search in Algorithm 1.

Algorithm 1: Output Clickstream Search

```
input  : Decoder outputs $(o_1, o_2, ..., o_m)$,
         Number of candidates $k$
output: k clickstream candidates with highest probability
begin
    Initialize empty clickstreams list
    for $o \in (o_1, o_2, ..., o_m)$ do
        Initialize empty candidates list
        for clickstream ∈ clickstreams do
            for page ∈ o) do
                candidates.append([clickstream.append(page),
                  $log(p(\text{clickstream})) + log(p(\text{page}))$])
            end
        end
        ordered = descending order sort candidates by score
        clickstreams = ordered[:k]
    end
end
```

Remark The algorithm produces a heuristic output with given clickstream context. Combining with the *url2vec* model, the prediction can heuristically optimize the click path of a specific user since the embeddings are trained over all possible action path. For instance, a distraction advertisement page will not appear after optimization because the embedding of the advertisement page is far from the desired page if embeddings are learned correctly.

4 Experiment

> We must know. We will know.
>
> David Hilbert

In this chapter, we rationalize the process of our lab study based on the theory of human information behavior. Next, we construe the purpose of context-given web browsing tasks for our subjects.

The lab study took place during the last two weeks of November, from 14/11/2018 to 29/11/2018 in Frauenlobstrasse 7a, a faculty building of Ludwig-Maximillians-Universitaet Muenchen. Our action path data was collected by a self-developed embedded collector plugin installed in the mainstream browser, such as Google Chrome, on a self-provided desktop computer and a laptop.

In the lab study, we select three mainstream websites: Amazon, Medium, and Dribbble. These websites that cover categories for shopping, media consuming, and design brainstorming with design reasons (discussed later in Section 4.3). Then we manually designed 35 reasonable tasks and finally selected nine context-given browsing tasks (three for each website, discussed in Section 4.3) to simulate three different kinds of proposed browsing behavior, namely *goal-oriented, fuzzy and exploring behaviors*.

Each task requires participants to start from a starting page of a given website. The tasks do not restrict participants to using the given website only; they also allow participants to access websites outside the domain of hte landing page to help they complete the task (this information is provided to participants before participation). Participants start browsing after they completely understand the requirements of each task. No interruption or question answered during the task. If the time limit of a task exceeded, subjects can either acquire more time to accomplish the task or give up if they feel that the task is too difficult.

The study is designed as a within-subject study. Thus every participant performs all tasks. To eliminate the learning effect due the extensive duration of using same websites, we used a Latin square [Cochran and Cox, 1950] for the devices (desktop and laptop) and tasks participation order for our subjects.

Our lab study focused on 21 participants with a mean age of 23.04 (standard deviation of 3.216, min=18, and max=29). Of the participants, 10 were male and 11 were female. They were recruited anonymously and randomly selected via a mailing list.

4.1 Environment

The lab study used two self-provided devices: a desktop computer and a laptop. The reason for choosing two devices is that our study requires recording a complete clickstream during the study.

A major issue of mobile devices is that the operating system does not authorize the permission of allowance to collect data precisely over pages or user actions. Although Android devices can overpass system permission to privilege, the user behavior between iOS and Android devices has different personalities [Sandoiu, Ana, 2018]. Subjects exhibit [Reinfelder et al., 2014] abnormal awareness behavior regarding security and privacy issues when handling a newly provided Android device after they switch from an iOS device. Therefore, to eliminate this awareness, we focus our study environment on desktop devices, which allows us to collects the clickstream data from browsers with plugin supports.

All modern browsers support plugin development, Google Chrome [StatCounter, 2018] has 61.7% market of market share of desktop browsers, while Apple Safari only possesses 15.0% of the market. Google Chrome is therefore dominant the desktop web browser market.

Hence, we decided to use Chrome to establish our plugin for data collection. The questionnaire after our lab study indicates the subjects' browser usage share, as dupicted in Table 4.1. The result further support our browser selection.

Table 4.1: Browser usage shares of lab study subjects

	Google Chrome	**Apple Safari**	**Mozilla Firefox**	**Microsoft Edge**
Number	11	5	3	2
Percentage	52.38%	23.81%	14.29%	9.52%

4.2 Browsing Behaviors

Before we explain the design justification for our context-given browsing task, we first present and discuss three types of user browsing behavior: **goal-oriented**, **exploring** and **fuzzy**.

These three terminologies are aggregated and incorporated from behaviors that have been determined in former qualitative research on web browsing behavior. These terminologies are based on the fundamental theory of interdisciplinary perspective information seeking behavior [Wilson, 1997], which was discussed in Section 2.3. Table 4.2 compares the terminology differences between former research and our thesis.

Table 4.2: Terminology comparison of information behavior on the web

Author	**Terminologies**	**Terminologies**	**Terminologies**	**Main Factors**

[Choo et al., 1999]	Formal search	Conditioned viewing;
		Informal search
			Undirected viewing	Psychological; demographic;
				role-related environmental;
				source characteristics

[Johnson, Ross, 2017]	Directed browsing;
	Known-item search
		Semi-directed browsing;
		Explorative seeking;
		"You do not know what you need";
		Re-finding
			Undirected Browsing	Behavior

This thesis	**Goal-oriented**	**Fuzzy**	**Exploring**	**Purpose**

To justify our terminology, we combine the six qualitative activities from Ellis' Model [Ellis, 1989] and "information use" from Wilson's framework [Wilson, 1997] of information behavior theory to represent our summarized browsing behaviors as follows:

Goal-oriented behavior *occurs when a user initiates a visiting session on the web caused by a determined objective in a specific context*, such as business work, social communication, university study, literature research, and so on.

Goal-oriented behavior indicates a piece of active information behavior. Instead of *formal search*, that only covers the phase of "monitoring" and "extracting" (or *directed browsing* and *known-item search* that covers "browsing" and "differentiating" or "monitoring" and "extracting" respectively), goal-oriented browsing behavior contains the entire life cycle of human information behavior starts from "starting" phase. By observing a browsing behavior, a determined "information use" can be overserved and concluded.

For instance, a college student intentionally need a latest lecture slide (*information use* observed), the student then opens web browser, access college website (*starting*) and navigates to the lecture homepage (*chaining*, *browsing*, and *differentiating*). Finally, the student exit browsing after download the slides (*monitoring* and *extracting*).

Exploring behavior *occurs when a user initiates browsing session aimlessly with no clear observed extracting or information use during the session, the person greedily or breadth-first consumes and the content on the Web without any information extracting and information use*, such as media consuming, learning before using and so on.

Exploring browsing behavior indicates opposite behavior from goal-oriented browsing behavior. A more formal description of exploring behavior using Ellis' model, would note that the behavior represents "chaining" and "browsing" without "differentiating" and "extracting" from "starting" while information seeking.

For instance, a person who accesses an unknown utility web application (*starting*), may explore the functions one by one as well as what they can do while using the application (*chaining* and *browsing*).

Fuzzy behavior *occurs when a user initiates a visiting session for information use with non-systematic and incomplete prior knowledge that may involve ongoing browsing ongoing to update the framework of knowledge until final acquisition or abandon.*

Fuzzy behavior in browsing behavior is in between goal-oriented and exploring behaviors. Instead of only "chaining" and "browsing" from "starting", fuzzy behavior also engages "differentiating" or "monitoring" while information seeking.

For instance, a researcher may have heared a new technique proposed in another scientific field that may influence their research. That person may then opens a search engine (*starting* and *chaining*) to seek (*browsing*) existing (*differentiating*) follow-up research (*monitoring*). The browsing may end without information use because the technique is irrelevant to their research.

Remark Table 4.3 illustrates the existence of activities of our three forms of browsing behavior. Note that "information needs" is not suggested in Wilson's theory [Wilson, 1981] because they can not be clearly observed before information seeking but sometimes may be observed after information use. Therefore we do not take information need into the consideration of our terminologies.

Table 4.3: Existence of activities from Ellis' Model and information use in goal-oriented, exploring and fuzzy browsing behavior

Behaviors	Information Need	Information Seeking						Information Use
		Starting	Chaining	Browsing	Differentiating	Monitoring	Extracting	
Goal-oriented	N/A	Exist	Exist	Exist	Exist	Exist	Exist	Exist
Fuzzy	N/A	Exist	Exist	Exist	Exist	Exist		
Exploring	N/A	Exist	Exist	Exist				

4.3 Tasks Design

We designed 35 browsing tasks after conducting a pilot study. Nine tasks were selected for three websites: Amazon.com, Medium.com, and Dribbble.com because of the following reasons:

1. These three websites all have tasks that correspond to the three types of browsing behavior;
2. Each of the tasks can be finished in around 5 to 10 minutes according to the measurement of pilot study;
3. All these websites are mainstream websites that do not require significant professional domain knowledge to use.

In addition, the unselected tasks are listed in Appendix B.3.

4.3.1 Tasks of Goal-oriented Behavior

We designed and selected an appropriate goal-oriented task for selected websites. Each task is designed with three designed information needs as the justification for information use.

Amazon.com *Assume your smartphone was broken and you have 1,200 euros as your budget. You want to buy an iPhone, a protection case, and a wireless charging dock. Look for these items and add them to your cart.*

This task initiates from the homepage of Amazon (*starting* and *chaining*), and contains three determined objective since a subject is required to add three specific items to the cart (*information use*). There are a few hidden considerations behind the task (*browsing* and *differentiating*), which makes the task more realistic (*monitoring* and *extracting*): a) There is a budget for this task, which requires subjects to consider the price of items instead of simply adding the first recommended item to cart. b) the starting page is amazon.com instead of amazon.de. This decision requires subjects to consider the exchange rate between U.S. dollars and euros for budgeting. c) There are some items cannot be shipped to Germany (the study took place in Germany). Subjects cannot add these items to the cart and should find other alternatives.

Medium.com *Assume you are making plans for your summer vacation. You want to visit Tokyo, Kyoto, and Osaka. You want to find out what kind of experience other people have had when traveling to these three places in Japan. Your task is to find three posts on traveling tips regarding these cities. Elevate a post if it is one of your choices.*

This task contains three determined purposes because there are three fixed traveling destination (*extracting* and *information use*). The task also involves a few considerations that increase the required interaction between the task to subjects: a) The website only offers an English version. Some Japanese characters may appear in an article. Thus, a translation website may be used during the study (*starting* and *chaining*). b) An article may contain numerous nouns, such as toponyms. Search engines may used during the study (*browsing*). c) Articles, that require a membership to access, cannot be elevated (*differentiating*).

Dribbble.com *You are hired at a cloud computing startup company. You receive assignment to design the logo of the company. Search for existing logos for inspiration and download three candidate logos that you like the most.*

The task also has three determined purpose because subjects are required to download three candidate trademarks (*extracting* and *information use*). During the participation, subjects must take a few implicit facts in to account: a) Subjects who unfamiliar with the term “Cloud Computing” must visit other explainations to determine the vision and mission of this type of company (*starting*). Subjects who are already familiar with the term still need to compare the designs made by other competitors (*chaining*, *browsing* and *differentiating*). b) Subjects should aware that some of the designs shared on the website are not suitable for trademark or icon design (*monitoring*).

4.3.2 Tasks of Exploring Behavior

Exploring tasks simply do not provide any deterministic objective, and all websites have a exploring task that is designed for subjects.

Amazon.com *Look for a product category that you are interested in and start browsing. Add three items that you would like to buy to your cart.*

Although the task do not require any specific items from the subjects, the task remains to have three different purposes because participants must add three items to the cart. This task is aimless because: all the tasks are not specifically informed to participants. They either do not have the needs to buy items or had needs of buy a specific category but do not have a product candicate yet. In any case, the description of the task request participants to start from a product category (*starting* and *chaining*), which avoids goal-oriented buying of a specific product.

Medium.com *Visit a category you are interested in and elevate three posts that you like.*

This task has a similar reason to the one as discussed in Amazon.com's exploring task (*starting* and *chaining*). Medium is a media website. Hence, visiting a specific article that read before participation is relatively difficult because all the content that is showed to users is updated daily. Thus, this task can be considered to be an exploring task.

Dribbble.com *Explore Dribbble and download the three images you like the most while you browse.*

Dribbble illustrates designs by using the image gallery (*starting* and *chaining*). The major difference between Dribbble and Google Image Search is that Dribbble is a user-centered content aggregation website, while Google Image Search is a simple content aggregation engine. Hence, there will be two different interactions in Dribbble: exploring designs based on keywords and categories or exploring designs based on users. The latter helps its user to finding similar design style. The task is aimless because the task simply describes nothing and lets participants explore their preferences for design styles.

4.3.3 Tasks of Fuzzy Behavior

Each of our selected websites also has a fuzzy task, and there are three major goals for each task that act as control conditions to subjects' action paths in our experiment.

Amazon.com *You want to buy a gift for your best friend as a birthday present. Add three items to your cart as candidate.*

The clarity of the task is stronger than the exploring task but is weaker than the goal-oriented task, because the task restricts participants from adding items for a specific purpose (birthday present) but does not point to any specific product (no *extracting*).

Medium.com *Assume you have an occasion to visit China for business. You are free to travel to China for a week and want to make a travel plan for that time frame.. Your task is to determine what kind of experiences other people have had when visiting to secondary cities or towns in China, then decide on three cities you want to visit (excluding Beijing, Shanghai, Guangzhou, and Shenzhen). Elevate a post if it helped you to decide.*

The clearness of the task is stronger than exploring the task because it asks a participant to explore a non-deterministic direction of looking for secondary cities (no *extracting*). However, the clearness of the task is weaker than the goal-oriented task because the secondary cities described in Medium's user posts are unclear, and participants are supposed to make decisions themselves. Furthermore, this task pertains to traveling around China for a week. Cities cannot be randomly selected because makeing travel plans requires consideration of a city's geographic location.

Dribbble.com *You are preparing a presentation and need one picture for each of these animals: cat, dog, and ant. Download the three pictures you like the most.*

The task has three purposes of downloading images of animals, which restricts participant to a specific direction. Thus, the clearness of the task is stronger than the exploring task. However, the task describes a scenario of using these images in a presentation. Hence participants must consider the continuity of the design style, which makes the clearness of the task weaker than the goal-oriented task (no *extracting*).

5 Evaluation

> If a machine is expected to be infallible, it cannot also be intelligent.
>
> Alan Turing

In this chapter, we conduct evaluations of our collected data. The data is collected from 21 subjects, and 189 clickstream data are collected in total. Each clickstream contains action-level data with a stay duration of a specific page, for instance, we still collect a URL as a step of clickstream if a participant uses back button rollback to a previously visited page without requesting server. A clickstream also has a subjective difficulty score from the questionnaire (shown in Appendix B) after the completion of each task.

5.1 Subjective Task Difficulty

This section discusses the subjective task difficulty qualitatively and quantitatively. Figure 5.1 illustrates a normalized (raw scores are listed in Appendix C Table C.1) subjective difficulty score with respect to all tasks.

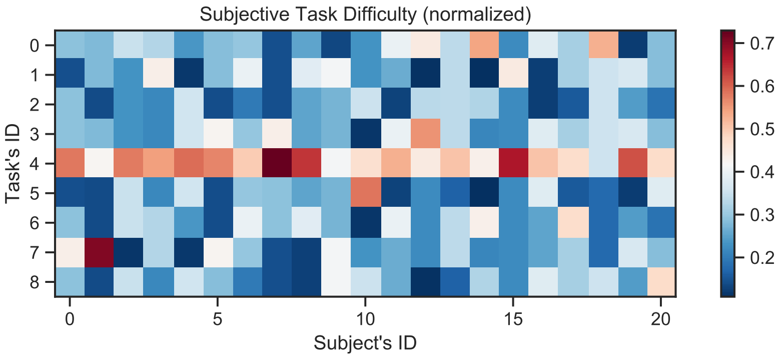


Figure 5.1: Subjective difficulty score: each column indicates an individual subject and each row indicates a browsing task. Tasks from 0 to 8 represent Amazon Goal Oriented Task, Amazon Fuzzy Task, Amazon Exploring Task; Medium Goal Oriented Task, Medium Fuzzy Task, Medium Exploring Task, Dribbble Goal Oriented Task, Dribbble Fuzzy Task, and Dribbble Exploring Task respectively. From this heat map, one can observe Medium Fuzzy Task is the most challenging task according to the subjects voted subjective difficulty, a Mann-Whitney U significant test justifies this observation.

To generalize the task difficulty, the null hypothesis (H_0): the difficulty of fuzzy task is not greater than exploring task and alternative hypothesis (H_1): the difficulty of fuzzy task is greater than exploring task. We conduct non-parametric one-tailed Mann-Whitney U test [Mann and Whitney, 1947], under null hypothesis, $p = 2.54 \times 10^{-5} < 0.05$, reject H_0. Similarly, we compare difficulty score on goal oriented task and exploring task (with corresponding hypothesis, $p = 0.00534 < 0.05$), difficulty score on fuzzy task and goal oriented task (with corresponding hypothesis, $p = 0.0145 < 0.05$), all rejects H_0. Therefore we concludes the task difficulty is ordered as follows: *difficulty of fuzzy task* $>$ *difficulty of goal oriented task* $>$ *difficulty of exploring task*, which means exploring tasks have lower effort in clickstream, and effort of doing fuzzy task gains highest effort.

5.2 Browsing Behavior Classification

As discussed in Section 4.3, we described three type of browsing behavior. In this section, we provides two type of evaluations to interpret the browsing behavior classification.

First, we evaluate the indication of general features browsing behavior, features including difficulty of task, number of actions in a clickstream as well as the total stay duration in a clickstream. Then we implements our action path model by using the action-level clickstream data and stay duration of each page, which was described in Section 3.3.3 and 3.3.4.

5.2.1 Interpretation based on General Features

As a baseline of our classification performance, we use the **completion efficiency**, **total time duration of a task** as well as **total number of actions of a task** as the three features for browsing behavior classification.

Note that the completion efficiency is defined by the shortest path of entire clickstream, and the completion efficiency cannot can only be determined if and only if the clickstream is given, in a sense, it carries a latent information of browsing behavior.

We applied gird-search on support vector machine (SVM) with polynomial kernel, the best classification precision is 0.53 ($C = 4.5, \gamma = 1.5$), and the micro average F1 score is also 0.53, which is better than random (0.33).

To understand the meaning of classification, we also applies a randomized decision tree that gives the importance of the used features: *total time duration and number of actions of a task is more important than our self defined completion efficiency.*

More specifically, we applies one-tailed Mann-Whitney U test for each of the features, for instance the null hypothesis (H_0): the completion efficiency of goal-oriented task is not greater than exploring task, we have $p = 0.0019 < 0.05$ reject H_0, which means the completion efficiency of goal-oriented task is significant efficient than than exploring task.

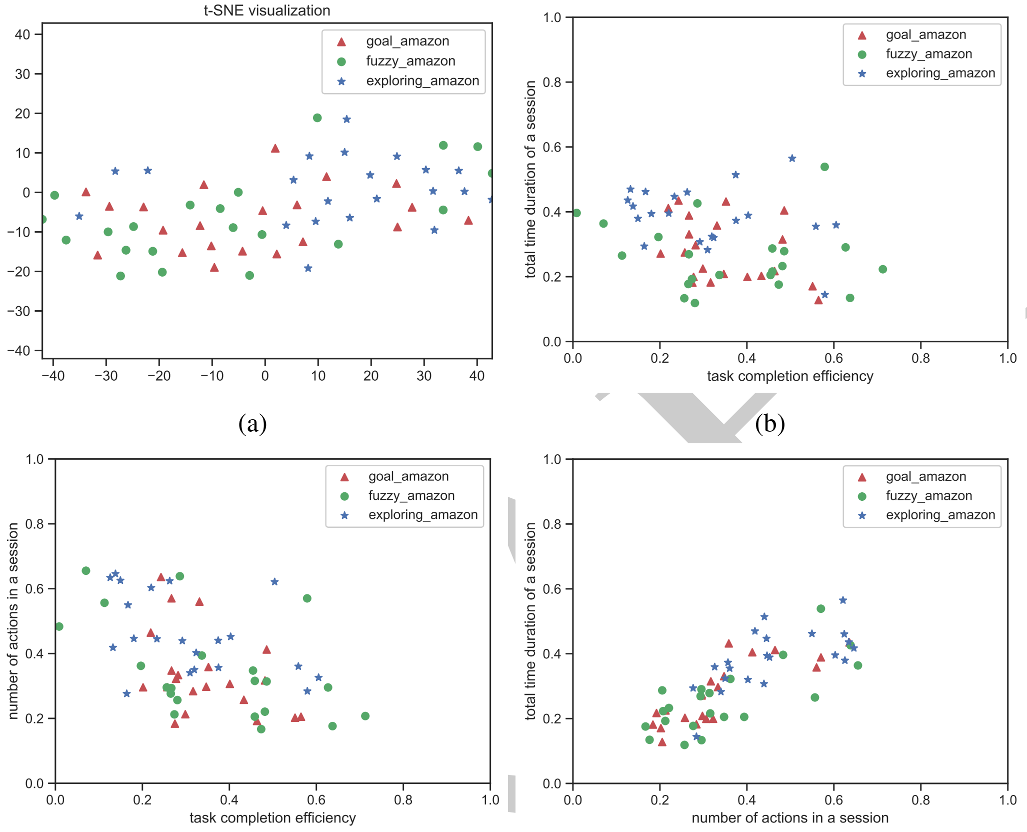
Similarly, we conduct the significant test with similar hypothesis to all comparable combinations as showed in Table 5.1, 5.2, and 5.3.

Table 5.1: One-tailed significant test for completion efficiency in different browsing behaviors. The null hypothesis in this table, for instance, completion efficiency of fuzzy task is *not* significant efficient than goal-oriented task, the result $p = 0.45 > 0.05$ which means accept $H0$. Similar to others.

v.s.	efficiency goal	efficiency fuzzy	efficiency explore
efficiency goal	N/A	reject	reject
efficiency fuzzy	accept	N/A	reject
efficiency explore	accept	accept	N/A

Table 5.2: One-tailed significant test for total stay duration of a task in different browsing behaviors. The null hypothesis in this table, for instance, total stay duration of fuzzy task is *not* significant stay longer than goal-oriented task, the result $p = 0.41 > 0.05$ which means accept $H0$. Similar to others.

v.s.	duration goal	duration fuzzy	duration explore
duration goal	N/A	reject	reject
duration fuzzy	accept	N/A	reject
duration explore	accept	accept	N/A



(a)

(b)

(c)

(d)

Figure 5.2: In these figures, 5.2a shows the t-SNE projection of completion efficiency, total time duration and number of actions for three different behavior; 5.2b is a 2D comparasion of using completion efficiency and total time duration; 5.2c provides a 2D comparasion of using completion efficiency and number of actions; 5.2d shows a 2D comparasion of using number of actions and total time duration. From t-SNE visualization, we observed that exploring tasks tend to centralized on the right and goal-oriented tasks and fuzzy tasks tend to centralized on the left, which indicates that exploring behaviors tend to classifiable comparing to other two behaviors. According the rest of feature comparasion visualizations, the completion effeciency and total time duration contributes more on interpret exploring behavior, and the number of actions tent to contributes more on interpret goal-oriented task.

Table 5.3: One-tailed significant test for total number of actions of a task in different browsing behaviors. The null hypothesis in this table, for instance, total number of actions of fuzzy task is *not* significant performs more actions than goal-oriented task, the result $p = 0.019 < 0.05$ which means reject $H0$. Similar to others.

v.s.	actions goal	actions fuzzy	actions explore
actions goal	N/A	accept	reject
actions fuzzy	reject	N/A	accept
actions explore	accept	reject	N/A

As conclusions, we summarized that:

- **Completion efficiency**: the completion efficiency of goal-oriented and fuzzy behavior is significant efficient than exploring behavior;
- **Number of actions**: the number of actions of goal-oriented behavior is significant lower than fuzzy and exploring behaviors.
- **Total stay duration**: the total stay duration of explroing behavior is significant higher than goal-oriented and fuzzy behaviors.

Furthermore, the completion efficiency and total stay duration are the more important than others for indication of exploring behavior, and number of actions are more important than others for indication of goal-oriented behavior.

5.2.2 Intepretation based on Action Path

To use full capacity of our data, this section uses the entire clickstream and its corresponding page-level stay duration as input, three ending mark (<EOA_GOAL>, <EOA_FUZZY>, and <EOA_EXPLORE>) as classification outputs, and then implements a single GRU layer action path model to classify the three type of browsing behaviors.

Our training parameters are: The GRU latent dimension is 10, training process feeds 132 clickstreams as training data, 38 clickstreams as validation, then propagates 500 epochs with batch size of 32. In the training process, we use Adam optimizer, categorical corss-entropy loss as well as L1 and L2 regularizer with early stopping, the total number of trainable parameters is 90323.

In the end of training, we evaluates 19 clickstreams as testing dataset and archieved **100.00% accuracy** of browsing behaviors classification.

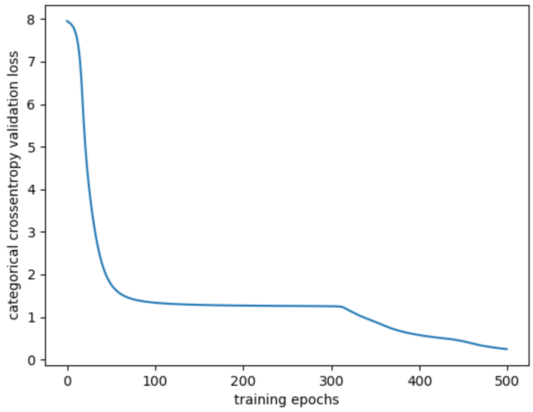


Figure 5.3: Categorical Cross-Entropy Validation loss curve while 500 epoches. The curves indicates the training process is not an overfitting since the loss is not increasing.

One can observed that the training process is not an overfit, and the validation loss is still not increase after 500 epoches, thus, single GRU layer action path model remains a large expressive generalization performance (100.00% accuate for three browsing behavior classification), therefore we expect to collect more data to verify whether the model applicable to a large dataset.

In addition, the action path model feeds the entire clickstream and time duration as inputs, therfore the entire clickstream contains informations regarding the number of actions as well as completion effeciency and more latent informations. Consequently, we conclude that the model works *perfectly on the classification of three different browsing behavior*. Since our experiment is only designed for three type of behavior, and the learning curve shows the model still has capacity and generalization ability to classify more precise categories of browsing behavior, a future investigation on more categories may be worthwhile.

5.3 Optimal Action Path Context

This section we evaluates our model with limited action path context, where the feeding action path are limited based on a split ratio. For instance, if a split ratio is 0.8 then we feed 80% of an action path into the model, then predict the rest of 20% actions. Figure 5.4 illustrates the best accuracy we archieved from a single layer action path model when use with different split ratio.

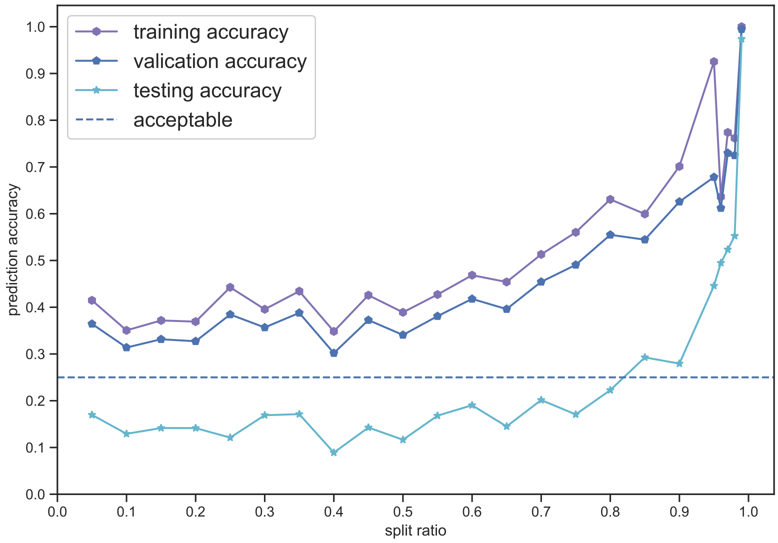


Figure 5.4: Prediction accuracy with limited context of input. This figure illustrates, wih more context of clickstream known to the action path model, more information to the model, and therefore much higher accuracy we can archieve. The accuracy we evaluated here is a greedy search accuracy, and thus higher than 25% of prediction accurate is acceptable, i.e. a quater of future movements are predicted correctly. On the right side of the figure, we archieved >60% accuracy of 3 to 5 future steps prediction. Classification is a special case in this figure where split ratio is equal to 0.99.

This figure illustrates, with more context of clickstream feeds into the action path model, the model receive more informations of the clickstream, and therefore much higher accuracy we can archieve for prediction. The accuracy we evaluated here is a greedy search accuracy, which performs element-wise comparasion between predicted clickstream and ground trueth clickstream, and the accuracy is the number of corrected predictions divided by total number of prediction steps.

An accuracy that higher than 25% is acceptable in our prediction task, since it indicates a quater of future movements are predicted correctly. On the right side of the figure, we archieved >60% accuracy of 3 to 5 future steps prediction.

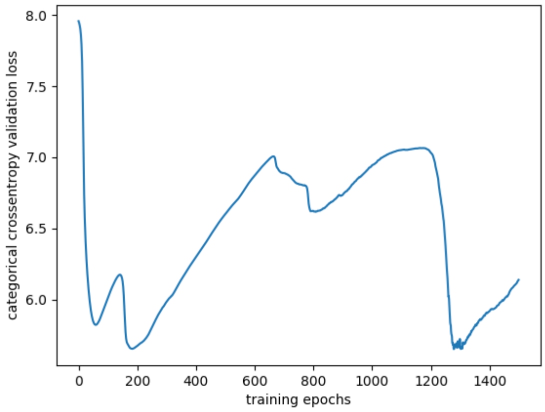


Figure 5.5: Validation loss curve when split ratio is 0.97. The loss indicates the model may be reparameterized while training and archieve better performance for predictions.

Note that the prediction is still not an overfitting to the dataset. Figure 5.5 illustrates the loss curve while training over 1500 epochs with 3 steps of prediction (split ratio 0.97). The loss starts increase after almost 200 epochs, which may be represent to overfitting, nevertheless, one can observe that the loss decreases down to similar level of early training and archieved a better performance (almost 60.0% of precision) than previous, which indicates the training process may reparameterize the action path model while training and archieve better performance for predictions.

5.4 Action Path Visualization

This section visualizes the actual action path of users and discusses the behavior qualitatively. In total, we collected 189 clickstream, which is not possible to illustrate all of them in the thesis, we selects the typical clickstreams to discuss and provids a visualization tool (see Appendix A) to help readers to explore all action paths.

5.4.1 Individual Common Patterns

Pattern of "cluster" The first pattern one can observe from the goal-oriented task clickstream is called "cluster". In Figure 5.6 and 5.7, the visualization shows different clustered intents in Amazon's goal-oriented task. Formally, *a pattern is called "cluster" if and noly if it is a partition of an action path that is connected with rest of the action path through a single node.*

We can easily discriminate the user browsing for different intent in different cluster, and then finally went to the cart without backtracking.

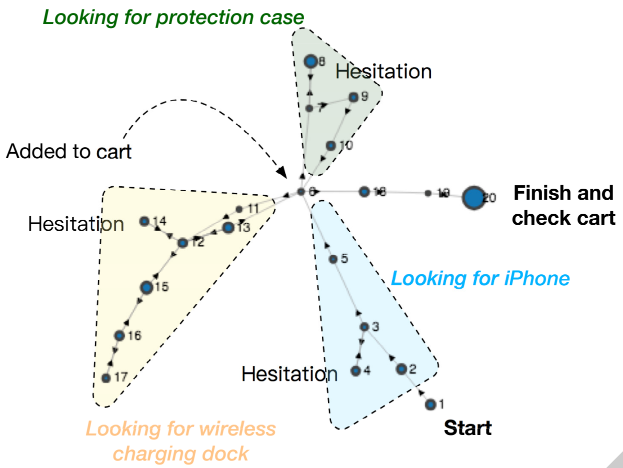


Figure 5.6: Patterns of cluster and hesitation of an action path. This figure visualizes an action path in goal-oriented Amazon's task. The visualized graph can be partitioned into four subgraphs and three of them are cluster pattern that is a representing of different shopping intent, which is exactly as same as the task design. Further, each cluster contains a hesitation pattern as labeled in the figure, for instance, node labeled with 4, 8, 14 are hesitation. Besides, the number of a node is a representative of chronological serial number of user actions.

Pattern of "hesitation" Beyound the cluster pattern, we also observes "hesitation" pattern in goal-oriented tasks where a short child path branch from its parent node in each intent cluster, e.g. node 4, 8, 14 in Figure 5.6 and node 5, 16 in Figure 5.7, which suggests "hesitation" is a pattern that more often appears in goal-oriented task within a "cluster". Formally, *a pattern is called "hesitation" if and only if it is a acyclic list and not in a star that joint with a cluster or a ring and the number of its nodes is less than any of existed cluster.*

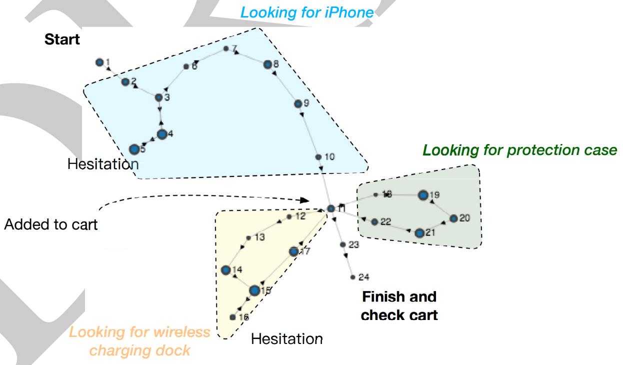


Figure 5.7: Patterns of cluster and hesitation of an action path. This figure visualizes an action path in goal-oriented Amazon's task. The visualized graph can be partitioned into four subgraphs and three of them are cluster pattern that is a representing of different shopping intent, which is exactly as same as the task design. Further, two of the clusters contain a hesitation pattern as labeled in the figure, for instance, node labeled with 5, 16 are hesitation. Besides, the number of a node is a representative of chronological serial number of user actions.

Pattern of "ring" and "star" Similarly, in fuzzy and exploring task, we observed two common pattern "ring" and "star" pattern is more often to appear in fuzzy and exploring tasks. Formally, *a pattern is called "ring" if and only if it is a list without connect to a cluster and starting node is not joint with ending node; a pattern is called "star" if and only if it is a spanning tree of an* *action path that a non-leaf node contains more than one child.*

Figure 5.8 illustrates an action path of Amazon's fuzzy task (purple nodes) and an action path of Dribbble's exploring task (orange nodes), both from same participants. One can observe "ring" and "star" patterns in the figure as highlighted through gray area surrounded by dashed line.

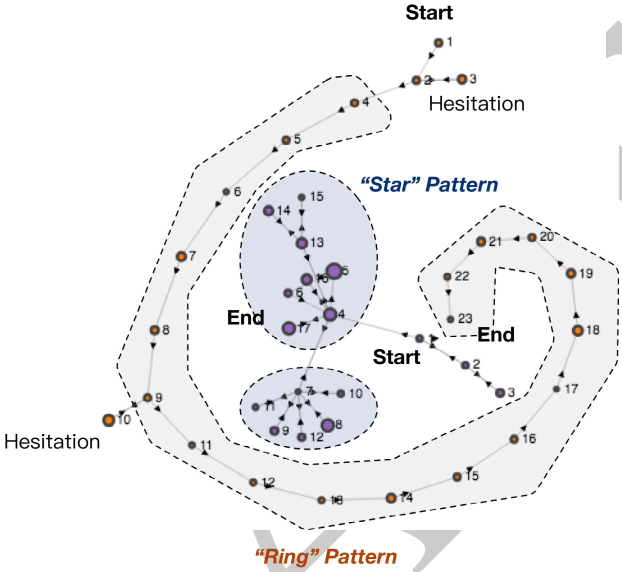


Figure 5.8: Patterns of ring and star of an action path. The figure visualizes an action path in Amazon's fuzzy browsing task (purple nodes) and Dribbble's exploring tasks (orange nodes). The visualized action path of exploring task is an linked list with few hesitations (node 3 and 10). The action path of fuzzy task contains two star patterns (roots are 4 and 7). As same as other visualizations, the number of a node is a representative of chronological serial number of user actions.

Similarly, as one more illustration, Figure 5.9 gives action paths in same tasks but from another participant that the purple nodes represents actions in Amazon's fuzzy task action path and orange nodes represents actions in Dribbble's exploring task action path.

In addition, even though we observed that the number of star pattern is more often to appear in fuzzy tasks and ring pattern is more often to appear in exploring tasks. We argue that this is because in fuzzy tasks, participants are able to identify the information uses, therefore the star pattern is more often to appear since it produces many backtracking behavior and causes the "differentiating" activity. However, in the exploring task, there is no explicit information uses described the exploring task, therefore participants keep exploring deeper and deeper from the starting page without backtracking, the star pattern appears when participant has multiple interests on different pages that referred from the same page.

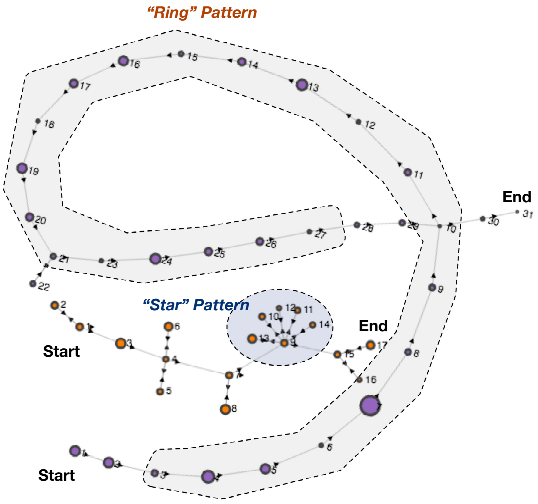


Figure 5.9: Patterns of ring and star of an action path. The figure visualizes an action path of a different participant in Amazon's fuzzy browsing task (purple nodes) and Dribbble's exploring tasks (orange nodes). The visualized action path of exploring task contains a star pattern where root is 9. The action path of fuzzy task contains a cyclic ring pattern that with a single hesitation in node 22. As same as other visualizations, the number of a node is a representative of chronological serial number of user actions.

In summary, we conclude that:

1. Goal-oriented browsing behavior contains common patterns of "cluster", and each cluster tend to indicate a specific intent;

2. Fuzzy and exploring behavior two common pattern of "ring" and "star", however, ring pattern is more often to appear in exploring behavior and star pattern is more often to appear in fuzzy behavior;

3. Pattern of "hesitation" usually attached to a cluster or a ring but not appear in a star.

5.4.2 Cross user Overlap Patterns

In the previous discussion we discovered the common patterns that appears in individuals. Nevertheless, it is still interesting to explore how action paths are manifest to multiple participants. Fortunately, we observed there are intersections among multiple subjects.

Pattern of "overlap" occurs when we observing action paths on multiple participants. Figure 5.10 and 5.11 are the the action paths visualized for same four participants in Medium's goal-oriented task and Dribbble's exploring task respectively. One can define a $n-$overlap ratio is the number of blacken nodes devided by total number of nodes in the action paths of n participants. Obviously, the maximum number of $4-$overlap ratio is 100.00%, and the minimum $4-$overlap ratio is 0.00%.

However, the highest $4-$overlap ratio and the lowest $4-$overlap ratio we observed from our dataset is 11.84% in goal-oriented task and 0.00% when compare two different tasks, therefore we argue that, the browsing behavior tend to be *user-specific* even users has same goal in a task, however they still share similar overlaps which suggests a *common interests*.

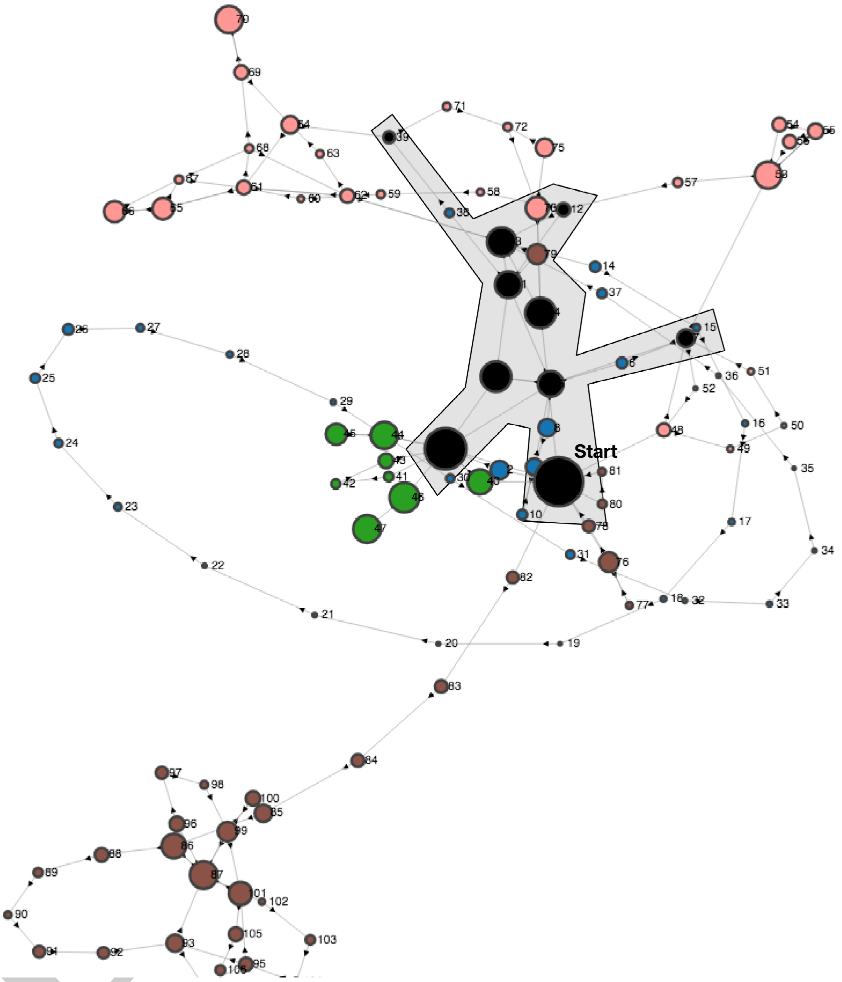


Figure 5.10: Example of "overlap" pattern in Medium's goal-oriented task: this figure visualize the clickstream intersection of four participants at Medium's goal-oriented task. Each color represents an individual clickstream except black nodes, which represents the overlapping of different clickstreams. The overlap ratio of this graph is 9.43%.

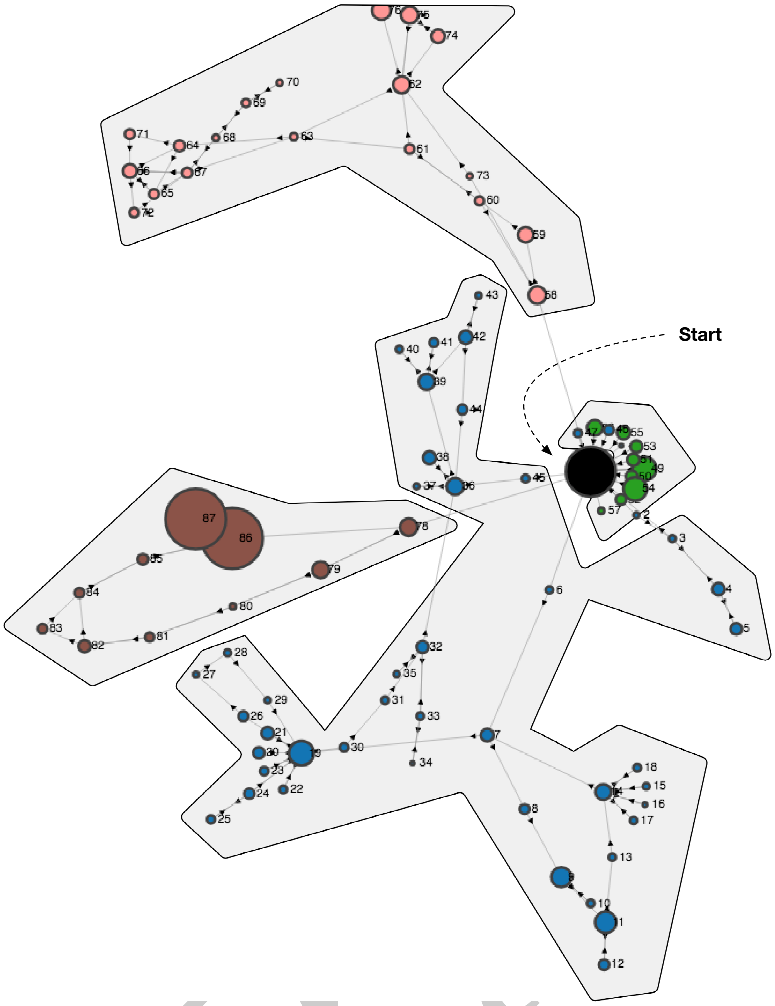


Figure 5.11: Example of "overlap" pattern in Dribbble's exploring task: this fugure visualize the clickstream intersection of four participants at Dribbble's exploring task. Each color represents an individual clickstream except blacken nodes, which represents the overlapping of different clickstreams. The overlap ratio of this graph is 1.15%.

In exploring task, the 4−highest overlap ratio is 1.15%, which is showed in Figure 5.11. The only common blacken node is the starting page. This observation suggests us that explroing browsing behavior is highly user-specific. Therefore, in conclusion, the overlap pattern of action path among multiple users suggests:

- Browsing behavior tend to be user specific, however we cannot confirm whether it is user-specifc because we have an issue with lack of data.
- Specifically, in goal-oriented browsing behavior, one can observe common interests between multiple subjects, whereas the exploring tasks has no intersection between subjects.

Remark Table 5.4 shows an analysis of all observed patterns based on Ellis' model, which explains why these patterns exists and how they contributes to our action path model.

- For "cluster" pattern, as we discussed before, information need can be observed from action path behavior, and the differentiating and monitoring contributes to the partitioning characer of the pattern and extracting and information then contributes to the short ring and single hesitations because the information are specified clearly.

Table 5.4: Existence of activities from Ellis' Model and information use in the observed patterns

Behaviors	Information Need	Information Seeking						Information Use
		Starting	Chaining	Browsing	Differentiating	Monitoring	Extracting	
cluster	observed				Exist	Exist	Exist	Exist
star			Exist	Exist	Exist			
ring		Exist	Exist					
hesitation	observed		Exist		Exist	Exist		
overlap	observed						Exist	Exist

- For "star" pattern, we can neither observe information need from action path nor did the participant uses information that find in star pattern. In Ellis' model, chaining, browsing and differentiating contributes to this pattern since the deptch from root to leaf node are small.
- For "ring" pattern, we also can neither observe information need or information use, the user explores deeper and deeper along the ring until the user exit the browsing session.
- For "hesitation", it connects to ring and cluster pattern, therefore they have common activities of chaining, differentiating and monitoring. However, information from hesitations are not used but one can easily observe the hesitation.
- For "overlap", we can observe common interests, which indicates inforamtion needs and use, the extracting and information use contributes more to represent this behavior.

Combining with Table 4.3, "cluster" pattern and "overlap" pattern essentially contributes to goal-oriented browsing behavior since they share common activities in this behavior, "star" and "ring" patterns contributes more on fuzzy and exploring tasks since their activities are more close to these browsing behaviors. Besides, as we discussed before, these patterns cannot be observed with explicit information use. The "hesitation" pattern appears in "star", "ring" and "cluster" pattern because they have common activities, such as "chaining" and "differentiating".

6 Applications

Simplicity is complicated.

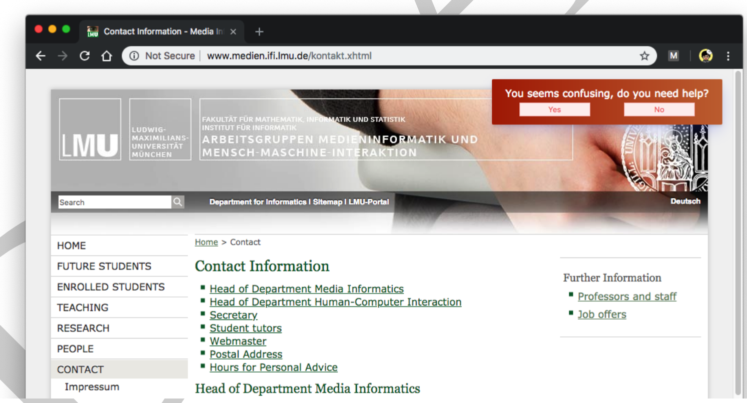
Rob Pike

In this chapter, we first introduce a possible application of our proposed model. This includes the implemented features, how the model could benefit a user, as well as the architecture and data flow of the application. In the second part of this chapter, we formalize and discuss the possibilities and benefits of being a standard web API for web developers and website designer.

6.1 Client-side Browser Plugin

We developed a client-side browser plugin as a illustration of our model application. The plugin is an intelligent system that proactively serves its user and provides proactive notifications based on the historical actions in a session when browsing behavior is detected to goal-oriented or fuzzy behavior, as illustrated in Figure 6.1.

The user can either select "Yes" and navigate to the most likely page that they will visit in the future, or select "No" to ignore the notification and mark it as an invalid detection. The plugin serves the user only if the browsing behavior is clearly detected to forbear massive notification that disturb the user. We argue that the plugin is only a supplement for improving browsing experience but is not always necessary. For instance in exploring behavior, a user's information need may not be clearly observed and the recommendations may not useful. One of the benefits of the plugin is to proactively help the user become efficient and reach the destination as fast as possible in the goal-oriented browsing.



You seems confusing, do you need help?

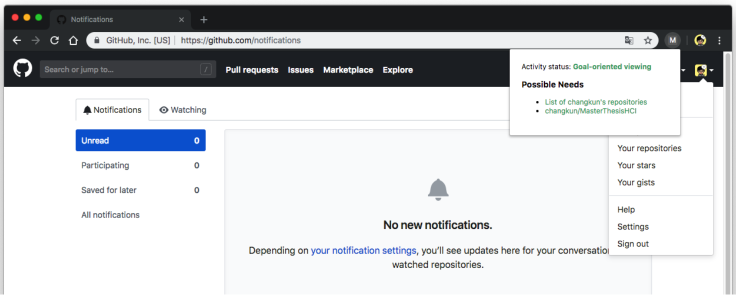
Contact Information - Media In
Not Secure | www.medien.ifi.lmu.de/kontakt.xhtml
Yes
No
LMU
LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN
FAKULTÄT FÜR MATHEMATIK, INFORMATIK UND STATISTIK
INSTITUT FÜR INFORMATIK
ARBEITSGRUPPEN MEDIENINFORMATIK UND MENSCH-MASCHINE-INTERAKTION
Search
Department for Informatics I Sitemap I LMU-Portal
Deutsch
HOME
FUTURE STUDENTS
ENROLLED STUDENTS
TEACHING
RESEARCH
PEOPLE
CONTACT
Impressum
Home > Contact
Contact Information
Head of Department Media Informatics
Head of Department Human-Computer Interaction
Secretary
Student tutors
Webmaster
Postal Address
Hours for Personal Advice
Head of Department Media Informatics
Further Information
Professors and staff
Job offers

Figure 6.1: Proactive notification: The plugin injects monitor script when the page is loaded, and then serve user giving notification when detecting fuzzy browsing behavior.

In Figure 6.2, other than proactive notification, users can always open a popup page provided by the plugin. The popup page enables another interaction that privides the predicted needs based on historical user actions. A user can always interact with the plugin and retrieve the possible needs and browsing status in the current session. This information is helpful to the plugin user because a user can understand the current status of web browsing, which implicitly allows the person to better focus on whether the person is detected as a form of exploring browsing behavior.

The implementation and architecture is not simple although it provides a small feature that exhibits context and future information for the user. Figure 6.3 illustrates the implemented architecture of the plugin.

First of all, the plugin daemon process will inject monitoring script (*step2*) intoto the newly opened page (*step1*). When the user starts browsing and interacting (*step3*), the injected script will



Activity status: Goal-oriented viewing

Possible Needs

- List of changkun's repositories
- changkun/MasterThesisHCI

No new notifications.

Depending on your notification settings, you'll see updates here for your conversatio watched repositories.

Figure 6.2: The plugin provided popup page: users can always open the page to understand the current status of browsing and predicted needs based on historical actions in a browsing session. In this case, the detected browsing behavior is under a goal-oriented browsing, and predicted actions are accessing the page of public GitHub repositories and accessing a specific repository.

report the referring of previous visited URL, current URL and stay duration to the daemon process of the plugin (*step4*).

Afterwards, the daemon process will report the referring information to the plugin server webhook (*step5*). Next, the webhook will immediately request the intra prediction microservice (*step6*) and result in a prediction (*step7*), which will then respond the prediction result to the daemon process with a pre-trained model (*step8*). Therefore the daemon process can decide if a proactive notification should be presented to the user or whether it should simply update its popup page for illustration (*step9*).

Since the prediction service received a new user action, it stores the action into a database subsequently for the model update (*step10*). Because of the cost of training a new model, the prediction service can decide to trigger the training service to retrain the model if it has already received enough new data (*step11*).

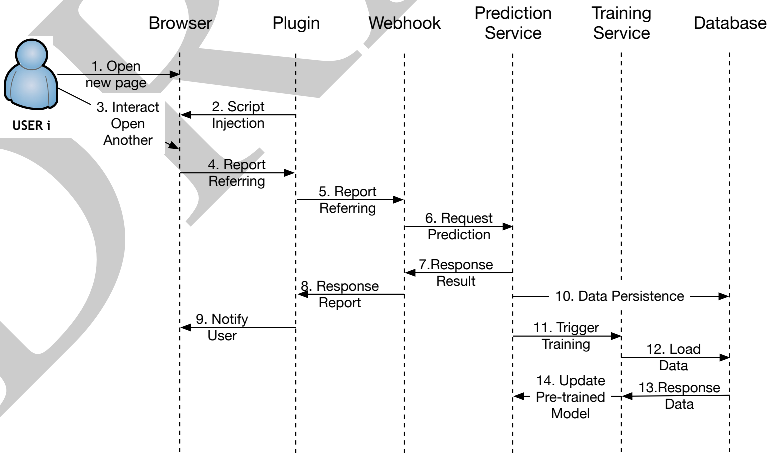


Figure 6.3: The implemented architecture of our plugin: This is the data flow illustration, Step 1 and 3 are user actions, and the rest of the steps are automatically triggered by each component of the plugin. For instance, the browser deamon process and plugin background process as two part of client-side components, the webhook, prediction service and training service are backend microservices running on a server.

Furthermore, the training service uses the pre-trained model as a base model to initiate the training by requesting newly created data from database (*step12* and *step13*), similar to the idea of transfer learning. After the training has achieved performance that is competitive to the pre-trained model, the training service will update the newly trained model to the prediction service (*step14*), which serves future prediction requests.

As we can observe from the architecture, the infrastructure is not as simple as the plugin feature intends to provide. Therefore, we argue that the plugin feature is a feature that only browser manufacturers can provide. In the following section, we formalize and discuss the possibilities of the plugin feature as a web API.

6.2 Web API Standardization and Platform-as-a-Service

Web API is a generic term used in various fields of development. Web API in the context of web browsers refer to the APIs provided by browser manufacturers to developers that helps with web applications. These APIs can even close help with manipulating hardware, for instance, WebAssembly [W3C, 2018].

Currently, there are experimental standard web APIs such as web speech APIs [Shires, Glen and Jaegenstedt, Philip, 2018] that integrate complex features to web developers and only have Google Chrome (after version 24) support. The specification proposal was initiated by Google. According to the source code of Chromium Kernel, the APIs are implemented based on the speech recognition service provided by Google Cloud Platform [1], which indicates that browser APIs do not only privide interfaces to the hardware but also access cloud platform services, i.e. Platform-as-a-Service integrated APIs.

The plugin that was illustrated in Section 6.1 can also be integrated as a PaaS API that is embedded into web browsers, which simplifies the infrastructure of the plugin. Developers can simply call the standardized API to report current user actions and obtain a response about current behavior status as well as the prediction of future movement or actions; see Figure 6.4 for the diagrams.

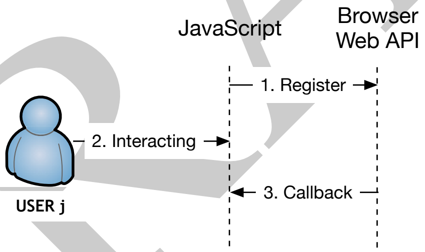


Figure 6.4: Usage overview of standadized BrowsingBehavior API

Defining the specification of the PaaS API aims enable web developers to use a web browser to monitor the future actions of their users. Developers can use the predicted actions to dynamically change the UI elements and improve the user experience of their product. We breifly discuss the non-normative web API design of the browsing behavior predictor, which seeks to keep the API to a minimum.

6.2.1 The *BrowsingBehavior* Interface

The browsing behavior interface is a scripted web API for resulting in a monitored browsing session, which is presented in Code 1.

```
[Exposed=Window, Constructor]
interface BrowsingBehavior : EventTarget {

    // methods to drive browsing behavior response
```

[1] https://github.com/chromium/chromium/blob/83928864c18362a4b0f84bad9bee4104f4655430/content/browser/speech/speech_recognition_engine.cc#L35, last accessed on January 03, 2019

```
    void start();
    void stop();
    void pause();
    void resume();

    // event methods
    attribute EventHandler onBrowsingStart;
    attribute EventHandler onBrowsingEnd;
    attribute EventHandler onBrowsingPause;
    attribute EventHandler onBrowsingResume;
    attribute EventHandler onResult;
}
```

Code 1: BrowsingBehavior Interface

***start()* method** When the start method is called, it represents the moment in time the web application wishes to begin monitoring user's actions. Then every step when a user was making moves, the *EventHandler onResult* will produce a standard prediction and classification of user browsing behavior. Further, the *EventHandler onBrowsingStart* will be called immediately after calling this method and before resulting a prediction result, which gives a barrier in between of calling *start* and callback *onResult*.

***stop()* method** When the stop method is called, it represents the instruction to browsing behavior service to stop monitoring user actions, and resulting in a final prediction in the *EventHandler onBrowsingEnd*.

***pause()* method** This method is used to ignoring the upcoming user actions to pauses the monitoring of user actions, and resulting in a prediction in the *EventHandler onBrowsingPause*.

***resume()* method** This method resumes the paused *BrowsingBehavior* object and recovers the monitoring of user actions. Before monitoring is fully recovered, the *EventHandler onBrowsingResume* will be called.

The primary consideration of designing these four methods is to restrict abuse of the APIs. Similar to cookie, speech recognition APIs, a website should acquire an authorization from their user; otherwise, the API cannot monitor any user actions on the web, which partially solves the issue of privacy and security. We will discuss more concerns about the feature in Chapter 7.

6.2.2 *onResult* callback

onResult callback passes the prediction after the browser user acted. The prediction result consists of two parts: behavior and future movements.

The *behavior* attribute of the result object is a JSON object that contains confidence level, i.e., classification probability, and a enumerate *category* attribute that indicate a finite set of user browsing behaviors, i.e., goal-oriented, fuzzy or exploring.

```
{
    "behavior": {
        "confidence": float64,
        "category": string,
    },
    "futures": [
        {
            "confidence": float64,
            "actions": array[string],
        },
        {
            "confidence": float64,
            "actions": array[string],
        },
        ...
    ]
}
```

Code 2: Result object of onResult callback

The *futures* attribute of the result object is an ordered JSON object that from the highest *confidence* to lowerest confidence and the *confidence* is a floating number from minimum 0 to maximum 1. Meanwhile, the *actions* attribute in a JSON object of an item of *futures* array is an array of possible actions of URLs that ordered in chronologic order, the first element represents the next immediate action, and the last element represents the final action in the session, as shown in Code 2.

```
{
    "device_id": string,
    "previous_url": string,
    "current_url": string,
    "stay_seconds": float64,
    "time": string
}
```

Code 3: Formation of browser collections

From the perspective of implementation, browser manufacturers collect data after developer calls *start()*. In Code 3, each time when a user performs an action, including open a new page, switch to another tab or backtrack to former page, will result in a JSON object that contains *device_id* a unique identifier that represents the device, *previous_url* the previous URL of the action, *current_url* the current URL of the action, *stay_seconds* the stay duration of *previous_url* and *time* string of the time of data creation.

7 Discussion

I think; therefore I am.

René Descartes

We proposed an action path model that models a sequence of user actions over web browsing and their decision time of each action simultaneously. Then we designed and conducted a user study that collects action paths from participants with different browsing behavior. We discuss our main findings, decisions and the limitations of this work in this chapter.

7.1 Main Findings

Clickstream Modeling The action path model combines an entire action level clickstream, and the stay duration of each action into action path encoder. Our quantitative results indicate that a simply model can easily classify existing three type of browsing behaviors with 100.00% of accuracy, i.e. goal-oriented, fuzzy and exploring. Even further, the model is able to universally (cross-user) predict 3 to 5 future visit page with given 95 percent of browsing context.

Browsing Behaviors and Patterns We concluded three browsing behaviors based on information behavior theory that describes three process of web browsing. Our qualitative analysis first interpret the total number of actions are more important to contributes the indication of goal-oriented behavior, and the total stay duration and completion efficiency are more important to indicate exploring behavior.

Afterwards, we also observed five patterns from client-side clickstream, the ring and star patterns appears in fuzzy and exploring tasks, ring pattern is more often in exploring task, and the star pattern is more often in fuzzy task because of differentiating of information use. A cluster pattern is an indication of an individual intent while browsing, and it may connects few hesitation pattern. The overlap pattern discovered in the collected action path gains a low overlap ratio, which suggests action path tend to be a user-specific behavior but reserve a small region as common interest in goal-oriented browsing behavior. Next, an analysis based on Ellis' model and Wilson's theory explored the relationship of these patterns to the proposed browsing behaviors, and these patterns partially represents a browsing behavior. Finally, since the model encodes the entire client-side clickstream and stay duration, the analysis also explains the qualitative reason of why our model archives such a good performance.

7.2 Decisions

Why the task difficulty is measured by self-rating scale rather than NASA-TLX? NASA-TLX does not providing more insights than action path to our model. As we analysed in Section 5.1, the major purpose of the measurement of task difficulty is to identify inappropriate tasks design (i.e. abnormal outlier) rather than the purpose of measuring cognitive load by using NASA-TLX. Our significant tests to the subjective self-rating scale of task difficulty supports our argument that these tasks are significant different than one another.

Whether NASA-TLX for cognitive load or self-rating scale for task difficulty is not able to be used in our machine learning model since they are impossible to be collected from unseen users in bootstrap phase. Though it is possible to construct a single subjective score as one of the inputs to the action path model, the model learns browsing behaviors from all collected data, which means if the model is trained based on a dataset with subjective score, then the dataset is biased by these scores and eventually reduces the generalization ability in a user-independent context.

Why leave-one-subject-out cross validation (LosoCV) is not applied in classification task? LosoCV is not necessary in our case. Research in a context of HCI performs a special LosoCV for a purpose of claiming a model is tested in which it has not seen any unseened user data before, and arguing this evaluation is a representative of bootstrapping performance of a model. However, this is an unfortunately inappropriate approach for model performance justification. LosoCV has been researched many years, statistical research [Xu et al., 2012] proves that LosoCV is asymptotically equivalent to k-Fold cross validation, which verifies a traditional wisdom that the performance of a model that evaluated by LosoCV tend to worth than k-Fold cross validation because LosoCV increases the variance of generalization error [Bengio and Grandvalet, 2004]. Therefore, Gao et al. uses model averaging technique (ensemble multiple models that trained through LosoCV when leave different subjects) developed a novel regularization technique [Gao et al., 2016] to help a model generalize better. Intuitively, when a model that intend to work in a user independent case, we are only interested in how well a model could fit universally, and how the performance could be changed when a model with fixed architecture applied to more subjects. More precisely, one can observe that LosoCV is essentially trained on a partial of dataset, which is a biased dataset to the training process of the model. Therefore, when we use the best model that gains minimum generalization bound is nothing else but a biased learning with a part of subjects. This is not claiming that LosoCV is unnecessary in any cases, the theoretical insights indicates that LosoCV is critical when a model must be applied in a security context since LosoCV provides how well could a model interpret highly correlated clusters to individual users and how good of a model could defense an unseen attacker.

For bootstrapping, it is completely non-interests and trivial to the industrial because the bootstrap in a context of recommending (our application) is valuable if and only if users do not leave the platform after their first arrival. Therefore, one can solve the bootstrapping by giving mainstream selection and mainstream preferences, then provide personalized recommendations after collecting a minimum required dataset since collecting data becomes fairly easy when a user continuously using a platform.

Why the experiment is designed under three aggregated browsing behavior instead of using the existing concluded four or more information seeking behaviors? The main reason of aggregating existing information seeking behaviors is to find the best classification ability and expand tasks design scope. In a intelligent system, we argue that acting a human being through machine must be precise enough, otherwise, it will reduce the user's motivation of using a intelligent system since it mis-acting a fallible human behavior. Therefore we expect the system must work extremely accurate in any cases for a simple classification task. In the perspective task design scope, the information seeking behaviors on the web are concluded in a general scenario for all kinds of websites. Designing a suitable task to characterize a browsing behavior in a specific website requires sophisticated thinking and clearly formalization of all stages separates two different behaviors. The boundary of existing behaviors are not qualitatively defined and a browsing behavior can assign in multiple categories simultaneously.

For instance, in Choo's theory [Choo et al., 1999], web browsing behaviors are categorized in four aspects: formal search, conditioned viewing, informal search and undirected viewing. The formal search and undirected viewing are similar to goal-oriented and exploring behaviors, which discriminate two extremes of web browsing. However, informal search was describing and conditioned viewing was describing "a good-enough search is satisfactory" and "browse in pre-selected sources" respectively. The fuzziness of "good-enough search", "satisfactory" and "browse in pre-selected" are not clear enough and subjectively concluded. This fuzziness in different categories of browsing behavior are magnified in Johnson's patterns [Johnson, Ross, 2017]. Therefore, to avoid this uncertainty of our task design, we indiscriminate the browsing behaviors in between of goal-oriented and exploring behaviors as an individual fuzzy behavior.

7.3 Limitations and Future Works

Lack of data This thesis has a limitation of the lack of data. Though we collected 189 clickstreams from 21 subjects, however, comparing to the baseline action path model with 90323 parameters in Chapter 5, the dataset is still a small dataset for the training and learning task. Moreover, the validation loss (in Figure 5.3) suggests our model remains large capacity to learn more categories of browsing behavior and prediction performance may be improved via reparametrization (in Figure 5.5), it is still fascinating to see the performance of our model on a large dataset, moreover, how this model can adapts to more information on the web, such as the topic of a page, and interpret more detail with attention mechanism.

Data collection Our work simulates three proposed browsing behavior through carefully designed browsing tasks. This method only limit to a small group of users, which is not an appropriate approach for a large dataset collection. We planned to conduct a field study that installs a clickstream collector during a week, however, there are only two subjects after our lab study are willing to participate in the field study.

Reinforcement learning appraoch As described in Chapter 3, the dataset that applies to our action path model is an action-level dataset, which means the sequence of URLs is necessarily a series of user actions. This could inspire us to use reinforcement learning approach to train an agent that could explore and learn the environment of the web. Eventually, the agent will be able to learn and optimize the experience of browsing on the web, which implicitly solves the problem of data collection and the lack of supervised data.

Privacy This work monitors an action level of clickstream, which stores all browsing history of a person on a third-party database, and hence brings a trust and privacy issue of the application. We positively argue that this is a trust issue between users and service providers. As we discussed in Chapter 6, browser providers collect the data anonymously, and users use the browser because of trusts, then world wide web consortium formalizes a standardized web API to developers for using this information, and as a browser user can either authorize developers to use this API or give an explicit rejection.

Proactive serving We are in the era that intelligent system surrounding us. The way we interact with an intelligent system is not as natural as we interact with other people. Communications or interactions between humans in a context does not require any trigger word, and a person can brush out a needs or reacts to another immediately. The action path prediction gives a working example that shows proactive serving is possible if we monitor the environment of web browsing. Therefore, it is interesting to study how a user could use this feature and how users react to the elimination of interaction trigger of an intelligent system.

8 Conclusions

> Every age has its own myths and calls them higher truths.
>
> Anonymous

This thesis proposed an action path model that describes client-side user clickstream, as known as action path. To justify our model, we designed nine browsing tasks for three qualitatively discussed browsing behavior based on the theory of information behavior, then held a user study for these tasks that simulates the behaviors. Afterwards, we applied the collected data from user study to our action path model and analysed the model performance to these data with comparison to traditional machine learning approach. Subsequently, we also visualized these data and closely discovered the common, individual and intersection patterns among client-side clickstream. As an application showcase, we illustrated a browser plugin that monitors client-side user clickstream to predict future movements of web browsing and discussed the benefits of this plugin. Furthermore, we presented a generic architecture communication flow and architecture of the plugin, as well as the possibilities of standardize the plugin feature as browser Web APIs to other developers.

Our finding answers the research questions that motivates this thesis:

Understanding (a) client-side collected clickstream is different than server side collected clickstream because of the existence of parallel visiting and multiple website visiting, three suggested browsing behaviors are: goal-oriented, fuzzy and exploring behaviors; (b) number of actions, total stay duration and completion efficiency cannot provide an accurate classifier for these three behaviors, but the number of actions are more important than others to indication of goal-oriented browsing behavior and other two features are more important to indicate exploring behavior; (c) the observed patterns in action path including cluster, hesitation, ring, star and overlap contributes to different browsing behaviors; (d) action path visually tend to be user-specific but remains common interests in goal-oriented behaviors.

Classification the proposed action path model is 100.00% accurate for the classification of three browsing behavior, which is trained on a user-independent dataset.

Prediction three to five future steps prediction can be accurately (>60%) predicted in a simplest action path model.

Our findings are generic and subservience. The model is an action level model that models sequence of user actions and time of decision makings (stay duration), which means it can be use on desktop and also can be implemented in context of a mobile devices, or even a outside the context of web browsing. Similar to other user behavior data, client-side user clickstream or user actions directly indicates movements of a user and how they making decisions. Understanding, interpreting and predicting these data not only improves the user experience when doing web browsing, but also useful to help users reducing useless browsing, better controls and manages their time. Moreover, by standardize the data processing process can formalize the feature to developers, and then help them using the behavior predictions to improve user experience of their products.

Traditional server collected clickstream data has been proved its high value in many fields. With our work we exposit the value one-step forward, and contributes to models and approaches that hope to bring ponderable research to the community and industry.

Appendix

All resources relates to the thesis are open source, they can be found publicly in [2]:

- Thesis homepage: `https://changkun.us/thesis/`;
- GitHub repostory: `https://github.com/changkun/MasterThesisHCI/`.

All related text, picture and video content are licensed under a Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License[3]. The other parts of the thesis (such as program source code) are licensed under a MIT Public License [4].

A Content of enclosed CD

1. */docs/* - Documents regarding scheduling and discussion during the thesis
2. */experiments/* - Raw user study designs, raw datasets collected from field study, pilot study and lab study in the thesis. Besides, analysis code to the collected dataset are located in this folder.
3. */keynotes/* - The raw keynote files of thesis commencement and defence presentation slides.
4. */src/* - Developed applications. This folder contains four applications that produced in the thesis: *crawler* is a web spider that collects then entire link relationships in medien.ifi.lmu.de; *gink* is a website that reponsible for crowdsourcing labeling tasks in the wild; *mortal* is the developed web plugin that mentioned in the chapter of application, it has a microservice server and three browser plugin derivatives including lab study collector, field study collector and browsing predictor;
5. */thesis/* - The LaTeXsource code of the thesis, as well as a compiled PDF version.
6. */LICENSE* - An MIT License to all enclosed source code in the CD
7. */README.md* - A brief description of the content enclosed in the CD

[2] The contents found from these links may be revised for improvements that slightly differ from contents from enclosed CD.

[3] `http://creativecommons.org/licenses/by-nc-sa/4.0/`

[4] `https://github.com/changkun/MasterThesisHCI/blob/master/LICENSE`

B Tasks and Questionnaire in Lab Study

B.1 Phase 1: Browsing Task

This section approximately takes 80 minutes.

In this study, you are asked to accomplish a series of tasks provided in the table below. Please read the following tips carefully before you do the task [5].

1. **Please start from the given starting page.** You can then visit any other page. For instance, if you find a task too difficult, you can visit any other websites that help you accomplish the task (e.g. Google as a search engine), but you should only use the browser.

2. The tasks are designed to take **5 10 minutes**. Do not feel stressed if you spend more time because you have 80 minutes in total to **do the 9 tasks**. You will be notified if you spend more than 10 minutes on a task. You can decide to go to the next task or spend some to accomplish the unfinished task.

3. **Close the browser before you start working on the next task.**

4. **Unfortunately, questions cannot be answered while doing the tasks. Please ask them before starting a task if something is not clear.**

B.1.1 Task Group 1: Amazon.com

Task Category: Shopping

1. Assume your smartphone was broken and you have 1200 euros as your budget. You want to buy an iPhone, a protection case, and a wireless charging dock. Look for these items and add them to your cart.

   Requirement to Finish: Click "Proceed to checkout" when you finished, exit the browser when you see the "sign in" page.

2. You want to buy a gift for your best friend as a birthday present. Add three items to your cart as candidate.

   Requirement to Finish: Click "Proceed to checkout" when you finished, exit the browser when you see the "sign in" page.

3. Look for a product category that you are interested in and start browsing. Add three items to your cart that you would like to buy.

   Requirement to Finish: Clicked "Proceed to checkout" when time is up, exit the browser when you see the "sign in" page.

How difficult was the task? (1 5, 1 means very easy, 5 means very difficult)

——, ——, ——

B.1.2 Task Group 2: Medium.com

Task Category: Media

[5] The order of the tasks are rearranged through Latin square, this section only illustrate one possible order of tasks

1. Assume you were making plans for your summer vacation. You want to visit Tokyo, Kyoto, and Osaka. You want to find out what kind of experience other people made when traveling to these three places in Japan. Your task is to find three posts for traveling tips regarding these cities. Elevate a post if it is one of your choices.

   Requirement to Finish: Write down three tips. Close the browser when you are finished.

2. Assume you got an occasion to visit China for business. You are free to travel to China for a week. You want to make a travel plan for touring China within a week. Your task is to find out what kind of experience other how people made when going to secondary cities or towns in China, then decide on three cities you want to visit (excluding Beijing, Shanghai, Guangzhou, and Shenzhen). Elevate if a post helped you make a decision.

   Requirement to Finish: Write down the names of the cities you decided. Close the browser when you are finished.

3. Visit a category you are interested in and elevate the post you like.

   Requirement to Finish: Close the browser when time is up.

How difficult was the task? (1 5, 1 means very easy, 5 means very difficult)
_____, _____, _____

B.1.3 Task Group 3: Dribbble.com

Task Category: Design

1. You are hired to a Cloud Computing startup company. You get an assignment to designing the logo of the company. Search for existing logos for inspiration and download three candidate logos you like the most.

   Requirement to Finish: Close the browser when you finished the download.

2. You are preparing a presentation and need one picture for each of these animals: cat, dog, and ant. Download the three pictures you like the most.

   Requirement to Finish: Close the browser when you finished the download.

3. Explore dribbble and download images you like the most while you browse.

   Requirement to Finish: Close the browser when you finished the download.

How difficult was the task? (1 5, 1 means very easy, 5 means very difficult)
_____, _____, _____

B.2 Phase 2: Questionnaire

This section approximately takes 10 minutes.

1. Age: _____

2. Gender: Female / Male

3. What is your study program or occupation?

4. What are the websites that you access mostly? List your top-5 (max 10, including private use).

5. What do you usually do when you access these websites? Shortly answer your case for all the websites you listed in above and name two common reasons, ordered by frequency. (For example, for YouTube, the most common reason could be “Just for fun”, the second most common reason “Looking for tutorial”. Then write as “Mostly for fun, sometimes for learning” below.)

6. Do you use bookmarks to save webpages that you have found through a search engine? If so, why?

7. Which browser do you use mainly on your PC or Mac? Chrome / Safari / IE / Microsoft Edge / Firefox / Others, the name is: ______

8. Would you like to participate in a follow-up study? The study will ask you to install a browser plugin for a week which anonymously records your browsing history. Yes / No

9. Do you have any feedback on this questionnaire?

B.3 Unselected Tasks

This section lists all designed tasks but unselected to lab study.

B.3.1 Goal-oriented Task

1. **www.github.com**: You are comparing three most popular frontend desktop frameworks: Electron / NW.js / ReactNative Desktop. Your goal is to find out the latest release download link.

2. **www.medien.ifi.lmu.de**: You are a fresh medieninformatik student major in HCI program. You wants to find out recommended first semester study plan provided by the program, then select "Human-Computer Interaction II" opened in WS18/19 and check previous "Human-Computer Interaction I" opened in SS18 and SS17.

3. **www.en.uni-muenchen.de**: You are a international student who want to apply economics program for your master study at LMU. Find the page for application requirement.

4. **www.ielts.org**: You live in Munich, you want to participate to IELTS test next year on Feburary. Looking for the entrace to register the examination. You must keep seeking and stop when you selected the first track of Feburary test.

5. **www.bloomberg.com**: You somehow heared about Bloomberg reported a news about China use tiny chips infiltrate U.S companies. You wants to find the article.

6. **www.reddit.com**: You are a fan of Marvel comics, you want to view some spoilers regarding a comming moive "The Avengers 4". Find latest three post that spoilers The Avengers 4.

7. **www.facebook.com**: You are a facebook user, and you have a wide social. However you don’t wants to see parenting information in your timeline, you wish to turn them off for a year from your timeline; then recently you start interested in ping pong, you want to join a related local group.

8. **www.twitter.com**: You lost your phone and phone number, and you bought a new one. However the old phone number was registered in your twitter account, you want to change it for your account safety. Please find the entrace to change your phone number and password. Then you becomes curious on twitter’s settings. You want to know how twitter use your data and prevent twitter collect your data.

9. **www.youtube.com**: You want to be a Youtuber. You wants to know how to earn money from making videos, and what should you concern when you publishing a video.

10. **www.google.com**: You can't access your gmail. You want to findout whether gmail are current malfuntioning or not. Contact instance messaging support.

B.3.2 Fuzzy Task

1. **www.github.com**: You were a senior developer. Your boss wants you write a report regarding the tends of current development techniques. You want to find the most three popular (top-3 stars) web backend Go frameworks and access their repository, write their name down on a paper when you decided.

2. **www.medien.ifi.lmu.de**: You are a fresh medieninformatik student. You wants to select three lectures, one seminar and one practicum for your study in WS18/19.

3. **www.arxiv.org**: Find the most recent published a overview paper for these three topics respectively: affective computing, convolutional neural networks, distributed consistency algorithm.

4. **www.google.com**: You want to know how google profiling you based on your history. Find your personality profile that created by Google.

5. **www.bloomberg.com**: You want to find the relevant news regarding the progress of China use tiny chips infiltrate U.S companies.

B.3.3 Exploring Task

1. **www.github.com**: Browsing github and select three github repository your most interested in.

2. **www.medien.ifi.lmu.de**: Browsing the website until time is up.

3. **www.en.uni-muenchen.de**: Browsing the website until time is up.

4. **www.ielts.org**: Browsing the website to see what you can do except register to examination.

5. **www.bloomberg.com**: Browsing the website until time is up.

6. **www.reddit.com**: Browsing the website until time is up.

7. **www.facebook.com**: Browsing the website until time is up.

8. **www.twitter.com**: Browsing the website until time is up.

9. **www.youtube.com**: Browsing the website until time is up.

10. **www.arxiv.org**: Browsing the website for categories you interested in until time is up.

11. **www.google.com**: Browsing google until time is up.

C Raw Data Illustration

C.1 Subjective Difficulty Score from Lab Study

Table C.1 illustrates the raw subjective difficulty score from all of our participants.

Table C.1: Subjective task difficulty from lab study

Subject ID	Amazon.com	Medium.com	Dribbble.com
0	2, 1, 2	2, 4, 1	2, 3, 2
1	2, 2, 1	2, 3, 1	1, 5, 1
2	3, 2, 2	2, 5, 3	3, 1, 3
3	3, 4, 2	2, 5, 2	3, 3, 2
4	2, 1, 3	3, 5, 3	2, 1, 3
5	2, 2, 1	3, 4, 1	1, 3, 2
6	3, 4, 2	3, 5, 3	4, 3, 2
7	1, 1, 1	3, 5, 2	2, 1, 1
8	2, 3, 2	2, 5, 2	3, 1, 1
9	1, 3, 2	2, 3, 2	2, 3, 3
10	2, 2, 3	1, 4, 5	1, 2, 3
11	3, 2, 1	3, 4, 1	3, 2, 2
12	4, 1, 3	5, 4, 2	2, 2, 1
13	2, 2, 2	2, 3, 1	2, 2, 1
14	5, 1, 3	2, 4, 1	4, 2, 3
15	1, 2, 1	1, 3, 1	1, 1, 1
16	3, 1, 1	3, 4, 3	2, 2, 3
17	2, 2, 1	2, 3, 1	3, 2, 2
18	3, 2, 2	2, 2, 1	1, 1, 2
19	1, 3, 2	3, 5, 1	2, 3, 2
20	3, 3, 2	3, 5, 4	2, 3, 5

C.2 Raw clickstream data

Code 4 is an illustration of the collected clickstream data. It intends to help readers to have better understanding of this thesis. The complete dataset can be found in the enclosed CD.

```

[
    {
        "task_id": 1,
        "clickstream": [
            {"user_id":1,"previous_url":"","current_url":"https://www.amazon.com/","stay_seconds":26.214,"time":"2018-12-03T19:44:19Z"},
            {"user_id":1,"previous_url":"https://www.amazon.com/","current_url":"https://www.amazon.com/s/ref=nb_sb_noss_2?url=search-alias%3Daps\u0026field-keywords=iphone","stay_seconds":10.712,"time":"2018-12-03T19:54:19Z"},
            {"user_id":1,"previous_url":"https://www.amazon.com/s/ref=nb_sb_noss_2?url=search-alias%3Daps\u0026field-keywords=iphone","current_url":"https://www.amazon.com/s/ref=nb_sb_noss?url=node%3D7072561011\u0026field-keywords=iphone+xs\u0026rh=n%3A7072561011%2Ck%3Aiphone+xs","stay_seconds":6.099,"time":"2018-12-03T19:54:25Z"},
            ...
            {"user_id":1,"previous_url":"https://www.amazon.com/gp/product/handle-buy-box/ref=dp_start-bbf_1_glance","current_url":"https://www.amazon.com/gp/huc/view.html?ie=UTF8\u0026increasedItems=C788d76cc-7a30-44cc-8041-85993f4d6716\u0026newItems=C788d76cc-7a30-44cc-8041-85993f4d6716%2C1","stay_seconds":10.282,"time":"2018-12-03T19:57:40Z"},
            {"user_id":1,"previous_url":"https://www.amazon.com/gp/huc/view.html?ie=UTF8\u0026increasedItems=C788d76cc-7a30-44cc-8041-85993f4d6716\u0026newItems=C788d76cc-7a30-44cc-8041-85993f4d6716%2C1","current_url":"https://www.amazon.com/gp/cart/view.html/ref=lh_cart_vc_btn","stay_seconds":1.886,"time":"2018-12-03T19:57:41Z"},
            {"user_id":1,"previous_url":"https://www.amazon.com/gp/cart/view.html/ref=lh_cart_vc_btn","current_url":"https://www.amazon.com/ap/signin","stay_seconds":71.552,"time":"2018-12-03T19:58:53Z"},
        ]
    },
    {
        ...
    },
    ...
]
```

Code 4: Formation of browser collections

Bibliography

References

[Aceto et al., 1994] Aceto, S., Delrio, C., Dondi, C., Fischer, T., Kastis, N., Klein, R., Strauss, A., and Corbin, J. (1994). Grounded theory methodology: An overview. *Handbook of qualitative research. Thousand Oaks: Sage Publications*.

[Amo Filvá et al., 2018] Amo Filvá, D., Alier Forment, M., García Peñalvo, F. J., Fonseca Escudero, D., and Casany Guerrero, M. J. (2018). Learning analytics to assess students behavior with scratch through clickstream. In *Proceedings of the Learning Analytics Summer Institute Spain 2018: León, Spain, June 18-19, 2018*, pages 74–82. CEUR-WS. org.

[Baumann et al., 2018] Baumann, A., Haupt, J., Gebert, F., and Lessmann, S. (2018). The price of privacy: An evaluation of the economic value of collecting clickstream data. *Business and Information Systems Engineering*.

[Benevenuto et al., 2009] Benevenuto, F., Rodrigues, T., Cha, M., and Almeida, V. (2009). Characterizing user behavior in online social networks. In *Proceedings of the 9th ACM SIGCOMM Conference on Internet Measurement*, IMC '09, pages 49–62, New York, NY, USA. ACM.

[Bengio and Grandvalet, 2004] Bengio, Y. and Grandvalet, Y. (2004). No unbiased estimator of the variance of k-fold cross-validation. *Journal of machine learning research*, 5(Sep):1089–1105.

[Brodwin, D., D. O'Connell, and M. Valdmanis., 1995] Brodwin, D., D. O'Connell, and M. Valdmanis. (1995). Mining the Clickstream. pages 101–106.

[Bucklin and Sismeiro, 2000] Bucklin, R. E. and Sismeiro, C. (2000). How sticky is your web site? modeling site navigation choices using clickstream data. Technical report, Working paper, Anderson School UCLA.

[Carr, 2000] Carr, N. G. (2000). Hypermediation: commerce as clickstream. *Harvard Business Review*, 78(1):46–47.

[Cavoukian, 2000] Cavoukian, A. (2000). Should the oecd guidelines apply to personal data online. In *A report to the 22nd international conference of data protection commissioners*.

[Chatterjee, Patrali and Hoffman, Donna L and Novak, Thomas P, 2003] Chatterjee, Patrali and Hoffman, Donna L and Novak, Thomas P (2003). Modeling the clickstream: Implications for web-based advertising efforts. *Marketing Science*, 22(4):520–541.

[Chi et al., 2017] Chi, Y., Jiang, T., He, D., and Meng, R. (2017). Towards an integrated clickstream data analysis framework for understanding web users' information behavior. *iConference 2017 Proceedings*.

[Cho et al., 2014] Cho, K., van Merrienboer, B., Gülçehre, Ç., Bougares, F., Schwenk, H., and Bengio, Y. (2014). Learning phrase representations using RNN encoder-decoder for statistical machine translation. *CoRR*, abs/1406.1078.

[Choo et al., 1999] Choo, C. W., Detlor, B., and Turnbull, D. (1999). Information seeking on the web: An integrated model of browsing and searching.

[Cochran and Cox, 1950] Cochran, W. G. and Cox, G. M. (1950). Experimental designs.

[Courtheoux, 2000] Courtheoux, R. J. (2000). Database marketing connects to the internet. *Interactive Marketing*, 2(2):129–137.

[Dijkstra, 1959] Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische mathematik*, 1(1):269–271.

[Ellis, 1989] Ellis, D. (1989). A behavioural model for information retrieval system design. *Journal of information science*, 15(4-5):237–247.

[Ellis et al., 1993] Ellis, D., Cox, D., and Hall, K. (1993). A comparison of the information seeking patterns of researchers in the physical and social sciences. *Journal of documentation*, 49(4):356–369.

[Ellis and Haugan, 1997] Ellis, D. and Haugan, M. (1997). Modelling the information seeking patterns of engineers and research scientists in an industrial environment. *Journal of documentation*, 53(4):384–403.

[Fisher and Julien, 2009] Fisher, K. E. and Julien, H. (2009). Information behavior. *Annual Review of Information Science and Technology*, 43(1):1–73.

[Friedman, Wayne and Weaver, Jane, 1995] Friedman, Wayne and Weaver, Jane (1995). Calculating cyberspace: tracking “clickstreams.”.

[Gao et al., 2016] Gao, Y., Zhang, X., Wang, S., and Zou, G. (2016). Model averaging based on leave-subject-out cross-validation. *Journal of Econometrics*, 192(1):139 – 151.

[Garg and Agarwal, 2019] Garg, A. and Agarwal, M. (2019). Machine translation: A literature review. *CoRR*, abs/1901.01122.

[Giannini, 1998] Giannini, T. (1998). Information receiving: A primary mode of the information process. *Proceedings of the ASIS Annual Meeting*, 35.

[Gindin, 1997] Gindin, S. E. (1997). Lost and found in cyberspace: Informational privacy in the age of the internet. *San Diego L. Rev.*, 34:1153.

[Goldfarb, 2002] Goldfarb, A. (2002). Analyzing website choice using clickstream data. In *The Economics of the Internet and E-commerce*, pages 209–230. Emerald Group Publishing Limited.

[Graves, 2012] Graves, A. (2012). Sequence transduction with recurrent neural networks. *CoRR*, abs/1211.3711.

[Gundala and Spezzano, 2018] Gundala, L. A. and Spezzano, F. (2018). Readers’ demanded hyperlink prediction in wikipedia. In *Companion Proceedings of the The Web Conference 2018*, WWW ’18, pages 1805–1807, Republic and Canton of Geneva, Switzerland. International World Wide Web Conferences Steering Committee.

[Hochreiter and Schmidhuber, 1997] Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, 9:1735–80.

[Huang et al., 2012] Huang, J., Lin, T., and White, R. W. (2012). No search result left behind: branching behavior with browser tabs. In *Proceedings of the fifth ACM international conference on Web search and data mining*, pages 203–212. ACM.

[Huang and White, 2010] Huang, J. and White, R. W. (2010). Parallel browsing behavior on the web. In *Proceedings of the 21st ACM conference on Hypertext and hypermedia*, pages 13–18. ACM.

[Johnson, Ross, 2017] Johnson, Ross (2017). Website Browsing Behavior Patterns. https://3.7designs.co/blog/2017/10/website-browsing-behavior-patterns. Accessed: 2018-12-29.

[Jozefowicz et al., 2015] Jozefowicz, R., Zaremba, W., and Sutskever, I. (2015). An empirical exploration of recurrent network architectures. In *Proceedings of the 32Nd International Conference on International Conference on Machine Learning - Volume 37*, ICML'15, pages 2342–2350. JMLR.org.

[Kammenhuber et al., 2006] Kammenhuber, N., Luxenburger, J., Feldmann, A., and Weikum, G. (2006). Web search clickstreams. In *Proceedings of the 6th ACM SIGCOMM Conference on Internet Measurement*, IMC '06, pages 245–250, New York, NY, USA. ACM.

[Kang, 1997] Kang, J. (1997). Information privacy in cyberspace transactions. *Stan. L. Rev.*, 50:1193.

[Lin et al., 2012] Lin, M., Lin, M., and Kauffman, R. J. (2012). From clickstreams to searchstreams: Search network graph evidence from a b2b e-market. In *Proceedings of the 14th Annual International Conference on Electronic Commerce*, ICEC '12, pages 274–275, New York, NY, USA. ACM.

[Liu et al., 2010] Liu, C., White, R. W., and Dumais, S. (2010). Understanding web browsing behaviors through weibull analysis of dwell time. In *Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval*, pages 379–386. ACM.

[Lori Lewis, 2017] Lori Lewis (2017). What Your Audience Is Doing When They're Not Listening To You. https://www.allaccess.com/merge/archive/26034/what-your-audience-is-doing-when-they-re-not. Accessed: 2018-12-28.

[Lori Lewis, 2018] Lori Lewis (2018). What Happens In An Internet Minute: 2018 Update. https://www.allaccess.com/merge/archive/28030/2018-update-what-happens-in-an-internet-minute. Accessed: 2018-12-28.

[Lourenço and Belo, 2006] Lourenço, A. G. and Belo, O. O. (2006). Catching web crawlers in the act. In *Proceedings of the 6th International Conference on Web Engineering*, ICWE '06, pages 265–272, New York, NY, USA. ACM.

[Lyons and Henderson, 2005] Lyons, B. and Henderson, K. (2005). Opinion leadership in a computer-mediated environment. *Journal of Consumer Behaviour: An International Research Review*, 4(5):319–329.

[Mandese, 1995] Mandese, J. (1995). Clickstreams' in cyberspace. *Advertising Age*, 66(12):18–18.

[Mann and Whitney, 1947] Mann, H. B. and Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *The annals of mathematical statistics*, pages 50–60.

[Meier and Elsweiler, 2016] Meier, F. and Elsweiler, D. (2016). Going back in time: An investigation of social media re-finding. In *Proceedings of the 39th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '16, pages 355–364, New York, NY, USA. ACM.

[Mikolov et al., 2013a] Mikolov, T., Chen, K., Corrado, G., and Dean, J. (2013a). Efficient estimation of word representations in vector space. *CoRR*, abs/1301.3781.

[Mikolov et al., 2013b] Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., and Dean, J. (2013b). Distributed representations of words and phrases and their compositionality. In Burges, C. J. C., Bottou, L., Welling, M., Ghahramani, Z., and Weinberger, K. Q., editors, *Advances in Neural Information Processing Systems 26*, pages 3111–3119. Curran Associates, Inc.

[Mobasher et al., 2001] Mobasher, B., Dai, H., Luo, T., and Nakagawa, M. (2001). Effective personalization based on association rule discovery from web usage data. In *Proceedings of the 3rd International Workshop on Web Information and Data Management*, WIDM '01, pages 9–15, New York, NY, USA. ACM.

[N and Ravindran, 2018] N, C. T. and Ravindran, B. (2018). A neural attention based approach for clickstream mining. In *Proceedings of the ACM India Joint International Conference on Data Science and Management of Data*, CoDS-COMAD '18, pages 118–127, New York, NY, USA. ACM.

[Novick, Bob, 1995] Novick, Bob (1995). Internet Marketing: The Clickstream. http:/www.im.com/archives/9503/0375.htmlhttp:/www.im.com/archives/9503/0375.html. Accessed: 2018-12-10.

[Padmanabhan et al., 2001] Padmanabhan, B., Zheng, Z., and Kimbrough, S. O. (2001). Personalization from incomplete data: What you don't know can hurt. In *Proceedings of the Seventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '01, pages 154–163, New York, NY, USA. ACM.

[Park et al., 2017] Park, J., Denaro, K., Rodriguez, F., Smyth, P., and Warschauer, M. (2017). Detecting changes in student behavior from clickstream data. In *Proceedings of the Seventh International Learning Analytics &#38; Knowledge Conference*, LAK '17, pages 21–30, New York, NY, USA. ACM.

[Reagle and Cranor, 1999] Reagle, J. and Cranor, L. F. (1999). The platform for privacy preferences. *Communications of the ACM*, 42(2):48–55.

[Reidenberg, 1996] Reidenberg, J. R. (1996). Governing networks and rule-making in cyberspace. *Emory LJ*, 45:911.

[Reidenberg, 1999] Reidenberg, J. R. (1999). Resolving conflicting international data privacy rules in cyberspace. *Stan. L. Rev.*, 52:1315.

[Reinfelder et al., 2014] Reinfelder, L., Benenson, Z., and Gassmann, F. (2014). *Differences between Android and iPhone Users in Their Security and Privacy Awareness*, pages 156–167.

[Rumelhart et al., 1988] Rumelhart, D. E., Hinton, G. E., and Williams, R. J. (1988). Neurocomputing: Foundations of research. chapter Learning Representations by Back-propagating Errors, pages 696–699. MIT Press, Cambridge, MA, USA.

[Sadagopan and Li, 2008] Sadagopan, N. and Li, J. (2008). Characterizing typical and atypical user sessions in clickstreams. In *Proceedings of the 17th International Conference on World Wide Web*, WWW '08, pages 885–894, New York, NY, USA. ACM.

[Sandoiu, Ana, 2018] Sandoiu, Ana (2018). Do Android and iPhone users have different personalities? https://www.medicalnewstoday.com/articles/314376.php. Accessed: 2019-01-04.

[Schneider et al., 2009] Schneider, F., Feldmann, A., Krishnamurthy, B., and Willinger, W. (2009). Understanding online social network usage from a network perspective. In *Proceedings of the 9th ACM SIGCOMM Conference on Internet Measurement*, IMC '09, pages 35–48, New York, NY, USA. ACM.

[Schonberg et al., 2000] Schonberg, E., Cofino, T., Hoch, R., Podlaseck, M., and Spraragen, S. L. (2000). Measuring success. *Communications of the ACM*, 43(8):53–57.

[Shimada et al., 2018] Shimada, A., Taniguchi, Y., Okubo, F., Konomi, S., and Ogata, H. (2018). Online change detection for monitoring individual student behavior via clickstream data on e-book system. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge*, LAK '18, pages 446–450, New York, NY, USA. ACM.

[Shires, Glen and Jaegenstedt, Philip, 2018] Shires, Glen and Jaegenstedt, Philip (2018). Web Speech API. https://w3c.github.io/speech-api/. Accessed: 2019-01-03.

[Skok, 1999] Skok, G. (1999). Establishing a legitimate expectation of privacy in clickstream data. *Mich. Telecomm. & Tech. L. Rev.*, 6:61.

[StatCounter, 2018] StatCounter (2018). Usage share of web browsers. http://gs.statcounter.com/browser-market-share#monthly-201811-201811-bar. Accessed: 2018-12-29.

[Sun and Xin, 2017] Sun, Y. and Xin, C. (2017). Using coursera clickstream data to improve online education for software engineering. In *Proceedings of the ACM Turing 50th Celebration Conference - China*, ACM TUR-C '17, pages 16:1–16:6, New York, NY, USA. ACM.

[Sutskever et al., 2014] Sutskever, I., Vinyals, O., and Le, Q. V. (2014). Sequence to sequence learning with neural networks. *CoRR*, abs/1409.3215.

[The Apache Software Foundation, 1995] The Apache Software Foundation (1995). About Apache: How Apache Came to Be. http://httpd.apache.org/ABOUT_APACHE.html. Accessed: 2018-12-10.

[Ting et al., 2005] Ting, I.-H., Kimble, C., and Kudenko, D. (2005). Ubb mining: Finding unexpected browsing behaviour in clickstream data to improve a web site's design. In *Proceedings of the 2005 IEEE/WIC/ACM International Conference on Web Intelligence*, WI '05, pages 179–185, Washington, DC, USA. IEEE Computer Society.

[Vassio et al., 2018] Vassio, L., Drago, I., Mellia, M., Houidi, Z. B., and Lamali, M. L. (2018). You, the web, and your device: Longitudinal characterization of browsing habits. *ACM Trans. Web*, 12(4):24:1–24:30.

[W3C, 2018] W3C (2018). WebAssembly Core Specification. https://webassembly.github.io/spec/core/bikeshed/index.html. Accessed: 2019-01-03.

[Walsh, John and Godfrey, Sue, 2000] Walsh, John and Godfrey, Sue (2000). The Internet: a new era in customer service. *European Management Journal*, 18(1):85–92.

[Wang et al., 2017] Wang, G., Zhang, X., Tang, S., Wilson, C., Zheng, H., and Zhao, B. Y. (2017). Clickstream User Behavior Models. *ACM Trans. Web*, 11(4):21:1–21:37.

[Wang et al., 2016] Wang, G., Zhang, X., Tang, S., Zheng, H., and Zhao, B. Y. (2016). Unsupervised clickstream clustering for user behavior analysis. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, CHI '16, pages 225–236, New York, NY, USA. ACM.

[Waterson et al., 2002a] Waterson, S., Landay, J. A., and Matthews, T. (2002a). In the lab and out in the wild: Remote web usability testing for mobile devices. In *CHI '02 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '02, pages 796–797, New York, NY, USA. ACM.

[Waterson et al., 2002b] Waterson, S. J., Hong, J. I., Sohn, T., Landay, J. A., Heer, J., and Matthews, T. (2002b). What did they do? understanding clickstreams with the webquilt visualization system. In *Proceedings of the Working Conference on Advanced Visual Interfaces*, AVI '02, pages 94–102, New York, NY, USA. ACM.

[Weller, 2018] Weller, T. (2018). Compromised account detection based on clickstream data. In *Companion Proceedings of the The Web Conference 2018*, WWW '18, pages 819–823, Republic and Canton of Geneva, Switzerland. International World Wide Web Conferences Steering Committee.

[Werbos, 1990] Werbos, P. J. (1990). Backpropagation through time: what it does and how to do it. *Proceedings of the IEEE*, 78(10):1550–1560.

[Williams and Zipser, 1989] Williams, R. J. and Zipser, D. (1989). A learning algorithm for continually running fully recurrent neural networks. *Neural computation*, 1(2):270–280.

[Wilson, 1981] Wilson, T. D. (1981). On user studies and information needs. *Journal of documentation*, 37(1):3–15.

[Wilson, 1997] Wilson, T. D. (1997). Information behaviour: an interdisciplinary perspective. *Information processing & management*, 33(4):551–572.

[Xu et al., 2012] Xu, G., Huang, J. Z., et al. (2012). Asymptotic optimality and efficient computation of the leave-subject-out cross-validation. *The Annals of Statistics*, 40(6):3003–3030.

[Yamakami, 2009] Yamakami, T. (2009). Inter-service revisit analysis of three user groups using intra-day behavior in the mobile clickstream. In *Proceedings of the 2009 International Conference on Hybrid Information Technology*, ICHIT '09, pages 340–344, New York, NY, USA. ACM.

[Yang et al., 2014] Yang, Z., Wilson, C., Wang, X., Gao, T., Zhao, B. Y., and Dai, Y. (2014). Uncovering social network sybils in the wild. *ACM Trans. Knowl. Discov. Data*, 8(1):2:1–2:29.

[Zaloudek, 2018] Zaloudek, J. (2018). User Behavior Clustering and Behavior Modeling Based on Clickstream Data. Master's thesis, Czech Technical University in Prague, Faculty of Electrical Engineering Department of Computer Science.

[Zhang et al., 2016] Zhang, X., Brown, H.-F., and Shankar, A. (2016). Data-driven personas: Constructing archetypal users with clickstreams and user telemetry. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, CHI '16, pages 5350–5359, New York, NY, USA. ACM.