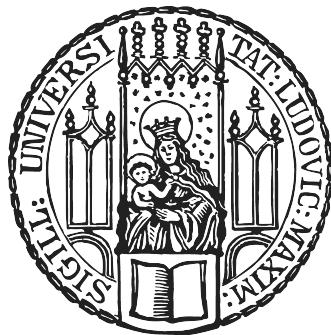


LUDWIG-MAXIMILIANS-UNIVERSITÄT AT MÜNCHEN
Department "Institut für Informatik"
Lehr- und Forschungseinheit Medieninformatik
Prof. Dr. Heinrich Hußmann



Masterarbeit

Understanding User Clickstream

Changkun Ou
hi@changkun.us

Bearbeitungszeitraum: 1.8.2018 bis 31.1.2019
Betreuer: Malin Eiband and Dr. Daniel Buschek
Verantw. Hochschullehrer: Prof. Dr. Heinrich Hußmann

Aufgabenstellung

DRAFT

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, January 6, 2019

Acknowledgments

I would like to appreciate Malin Eiband and Dr. Daniel Buschek for their great and constructive discussion, suggestion around thesis topic selection, model statements as well as their patient of given guidance to the thesis. The thesis would not be accomplished without them. Afterward, I am full of gratitude to Prof. Hussmann and Prof. Butz for offering me an unexpected opportunity to study aboard in Germany as well as their kindly helps in my academic period. Next, I wish to thank my best friend Yi, schoolfellow Yifei and Xingying, and former colleague Jin for their inspiring discussion surrounding my thesis. Finally, I will forever be beholden to my parents for their continuous supports while my postgraduate study, they dedicated their live to my better future.

DRAFT

DRAFT

Abstract

Early clickstream research emerges since the end of last century and has proliferated in the heart of our Internet world. Trades, public opinions, and almost every traces are precisely recorded on server side log files. The fundamental interaction between client and server stands immutably, despite the fact that mobile devices have governed our daily life. In this thesis, we proposed a model to characterize user browsing behavior while involving clickstream with multi-tab branching and backtrack actions on the Web, we call it Action Path model. To justify our model, we first established a lab study and collected clickstream data of individuals with manually designed nine different web browsing task for three mainstream websites based on the theory of information seeking behavior. Each website has three types of tasks, including goal-oriented, fuzzy and exploring browsing task, which characterized the corresponding three browsing behaviors. A collected clickstream of a subject consists of a timestamp based URL and the time duration of a single URL. By analyzing the subjects trace from our lab study, we seek to archive these goals: 1) Understanding: identify if browsing behaviors are distinguishable and finding common patterns that appears in clickstreams from subjects. 2) Classification: to separate and report browsing behaviors on the web, that help users better understanding their status. 3) Prediction: present the future click path more than one step with given context of browsing history in a session. To archive these goals, beyond justification analysis, we also developed a browser plugin as a possible application that predicts the future possible click under a visiting session and provides a score that indicates the probability of exploring. Furthermore, we generalize the design of our model and plugin communication protocol and discussed the possibility of formalizing them as standard Web APIs. To the best of our knowledge, this is the first study such detailed web browsing behavior modeling based on client-side clickstream.

DRAFT

Contents

1	Introduction	1
1.1	The Origin of Clickstream Research	1
1.2	This Thesis	2
2	Related works	3
2.1	Clickstream Behavior	3
2.2	Theory of Information Seeking Behavior	3
2.3	Theory of Sequence to Sequence Learning	3
3	Clickstream and Action-Path Models	5
3.1	Completion Efficiency	5
3.2	<i>url2vec</i> Embedding	6
3.3	Action-Path Model	7
3.3.1	Context Encoder	7
3.3.2	Context Decoder	8
3.3.3	Recurrent Unit	8
3.3.4	Ending Mark Interpretation	9
3.4	Action Path Optimization	10
4	Experiment	11
4.1	Environment	11
4.2	Browsing Behaviors	12
4.3	Tasks Design	12
4.3.1	Goal-oriented Task	12
4.3.2	Exploring Task	13
4.3.3	Fuzzy Task	14
5	Evaluation	15
5.1	Subjective Task Difficulty	15
5.2	Browsing Behavior Classification	15
5.2.1	Interpretation based on General Features	16
5.2.2	Interpretation based on Action Path	16
5.3	Optimal Action Path Context	17
5.4	Action Path Visualization	18
5.4.1	Individual Common Patterns	19
5.4.2	Cross-user Overlap Patterns	19
6	Applications	21
6.1	Client Side Browser Plugin	21
6.2	Standard Browser Web APIs	22
7	Discussion	23
8	Conclusions	23
8.1	Summary	23
Appendix		25
A	Content of enclosed USB	25

B Tasks and Questionnaire in Lab Study	25
B.1 Phase 1: Browsing Task	25
B.1.1 Task Group 1: Amazon.com	25
B.1.2 Task Group 2: Medium.com	26
B.1.3 Task Group 3: Dribbble.com	26
B.2 Phase 2: Questionnaire	27
B.3 Unselected Tasks	27
B.3.1 Goal-oriented Task	27
B.3.2 Fuzzy Task	28
B.3.3 Exploring Task	28
C Raw Data Illustration	29
C.1 Subjective Difficulty Score from Lab Study	29
Bibliography	29

1 Introduction

1.1 The Origin 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, business man 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 putforwards their method based on server recorded clickstream data. Note that a daily user is always allowed accesses parallel pages simultaneously and even switching across multiple websites for a browsing purpose. An obvious missing aspect of those papers is the server log data is incomplete to a characterizing visited user, and the log data only appropriate for a specific website. As an observation, our research no longer surveys server side clickstream, but focus and contributes to a client side collected

clickstream data for real visiting session of a user in a browser.

1.2 This Thesis

The main part of the thesis is structured in different chapters. 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 approaches for generic sequence learning, whose proposed in neural network research. Chapter 3 first defined the completion efficiency of a clickstream, then we formalizes our proposed sequence to sequence encoder/decoder model 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. Afterwards, in chapter 5, based on SVM, t-SNE and our proposed model, we conducte a quantitative analysis with described data from our lab study, the evaluation shows a very promising result and the result suggests TODO:. Moreover, we visualizes the clickstream through directed graph, by combining our traning model outputs, we also performs a qualitative analysis to all graphs, 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 into a communication protocol between client and server, and then the possibilities to being a standard Web API to developers. To conclude, we finally summarize the findings of our thesis, the existing drawbacks of our study, as well as the possible future improvements and directions of the thesis in the final chapter.

2 Related works

Related works section

2.1 Clickstream Behavior

2.2 Theory of Information Seeking Behavior

2.3 Theory of Sequence to Sequence Learning

DRAFT

DRAFT

3 Clickstream and Action-Path Models

In this chapter, we first formalize few concepts and metrics in clickstream data, and then describe a proposed clickstream model named *Action-Path model* based on recurrent neural network that models a client side clickstream behavior. The action path is different than clickstream since a user may uses *back button* or *switch browser tabs* then jumps to visited web pages or parallel web pages, namely, a user performed a visit action. A server side 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 user actions (with backbutton and browser tab switch effects) in a browser. Figure 3.1 illustrates a simplified version of action path that compares vanilla clickstream.

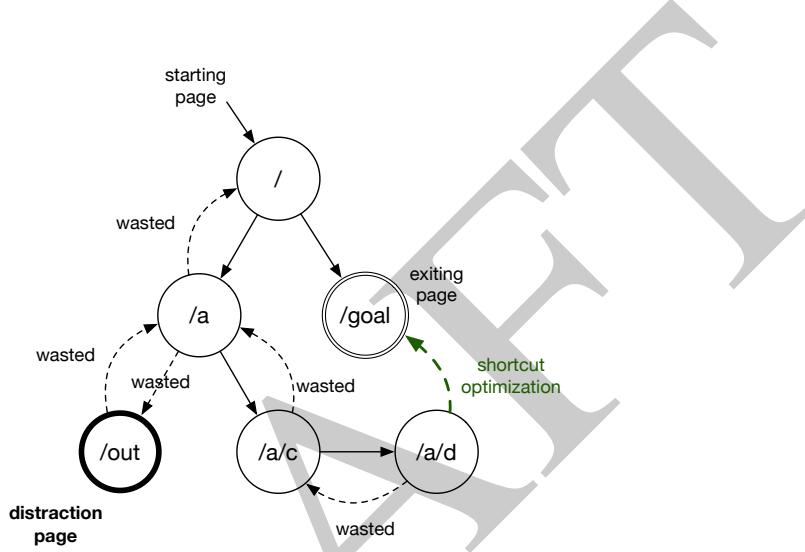


Figure 3.1: A simple action path. A user starts from the starting page, and performed a series of page click actions, ends on a exiting page. The server side records clickstream in the following order: $/ \rightarrow /a \rightarrow /out \rightarrow /a/c \rightarrow /a/d \rightarrow /goal$. However the actual user actions are: $/ \rightarrow /a \rightarrow /out \rightarrow /a \rightarrow /a/c \rightarrow /a/d \rightarrow /a/c \rightarrow /a \rightarrow / \rightarrow /goal$. The records on server side lost interaction details between users and browsers. Note that $/out$ is a distraction page in the graph, which may located in a different website (e.g. advertisement), and dashed arrows 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 actions is $/ \rightarrow /a \rightarrow /a/c \rightarrow /a/d \rightarrow /goal$.

For a convinience of discussion, we indiscriminate the use of term *action path* and *clickstream* in this chapter to indicate a series of user actions.

3.1 Completion Efficiency

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

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

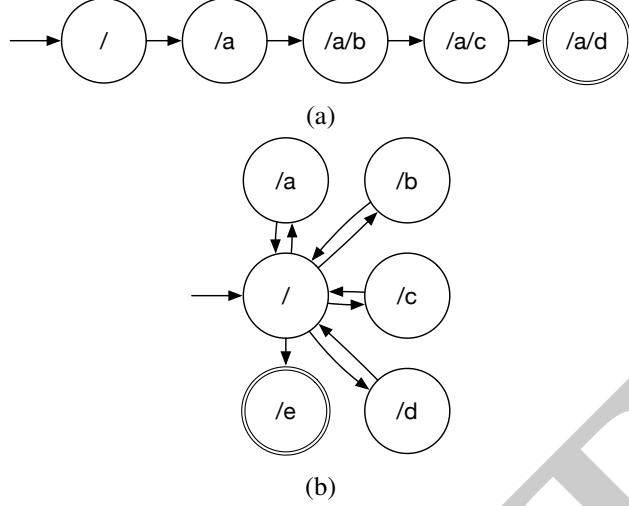


Figure 3.2: Two special case of an action path: linked list action path 3.2a, and 1-to-n bipartite graph action path 3.2b.

Let an action path is represented on directed cyclic graph, each node represents a visited page, and each edge has a weight that represents the stay duration of its tail node. Assume the total stay duration of the shortest path from starting page to 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 , the *completion efficiency* E is defined as follows equation 1:

$$E = w_1 \frac{n_s}{N} + w_2 \frac{d_s}{D} \quad (1)$$

$$w_1 + w_2 = 1$$

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

Remark 1. The definition of completion efficiency uses the term of shortest path, which is the problem of finding a path between the starting page and exiting page in a action path (directed cyclic graph) such taht the sum of the stay duration of its constituent pages in minimized. The problem can be solved by Dijkstra's algorithm [Dijkstra, 1959].

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

3.2 *url2vec* Embedding

The distributed representation of word2vec models achieve better performance in natural language processing, Mikolov et al. [Mikolov et al., 2013a] introduced continous bag-of-word (CBOW) and skip-gram model as an efficient method for learning high-quality vector representation of words, and CBOW is faster while skip-gram is slower but get better performance for infrequent words. We convey similar idea from these models and propose our *url2vec* model for client side clickstream data.

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

$$\begin{aligned}
& \frac{1}{T} \sum_{t=1}^T \sum_{-c \leq i \leq c, i \neq 0} \log p(\text{URL}_{t+i} | \text{URL}_t) \\
p(\text{URL}_{t+i} | \text{URL}_t) &= \frac{\exp(v_{\text{URL}_{t+i}}^\top v_{\text{URL}_t})}{\sum_{\text{all URLs}} \exp(v_{\text{URL}_{t+i}}^\top v_{\text{URL}_t})}
\end{aligned} \tag{2}$$

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 $v_{\text{URL}_{t+i}}$ is the vector embedding of output representations.

Remark 1. This model described by equation 2 is actually a three layer neural network: input layer of one-hot encoded 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 2 is impractical due to $\nabla \log p(\text{URL}_{t+i} | \text{URL}_t)$ is as large as 10^5 to 10^7 , two numerical optimizations based on Hofmann Tree and Negative Sampling are proposed by Mikolov et al. [Mikolov et al., 2013b].

3.3 Action-Path Model

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, \dots, i_T) , the original RNN computes a sequence of outputs (o_1, o_2, \dots, o_T) by interating the activation function 3:

$$o_t = W_{oh} \sigma(W_{hi} i_t + W_{hh} o_{t-1}), t = 1, 2, \dots, T \tag{3}$$

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 original 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 issue of the original 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 and estimates the conditional probability of $p(o_1, o_2, \dots, o_{T'} | i_1, i_2, \dots, i_T)$ where (i_1, i_2, \dots, i_T) is an input sequence, $(o_1, o_2, \dots, o_{T'})$ is a corresponding output sequence, and T is not required to be equal with T' . Our model convey similar idea from it.

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

3.3.1 Context Encoder

Our action path model consist a context encoder and a context decoder. Context encoder encodes URLs one by one and produces a context tensor that encodes the historical user actions, shown in Figure 3.3. In the encoder, we insert a starting mark "*<SOA>*" (*Start of Action*) as a sign of start feeding URLs, and a trigger mark "*<COI>*" (*Change of Intention*) as a sign to trigger decoder to decodes encoded context tensor.

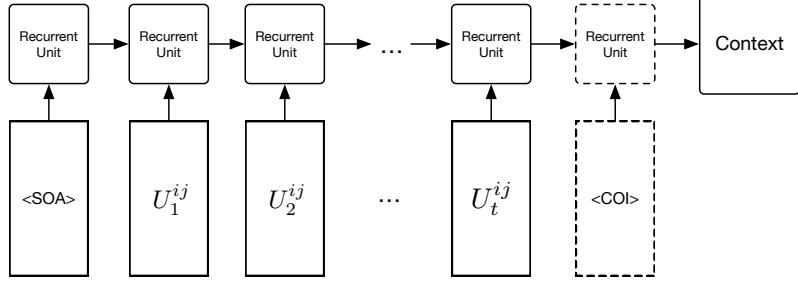


Figure 3.3: Context encoder of Action Path Model. In the encoder, a starting mark "<SOA>" is used as a sign of start feeding URLs, and a trigger mark "<COI>" as a sign to trigger decoder to decodes encoded context tensor. The trigger mark is automatically inserted after the k -th URL in the end of encoder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

3.3.2 Context Decoder

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

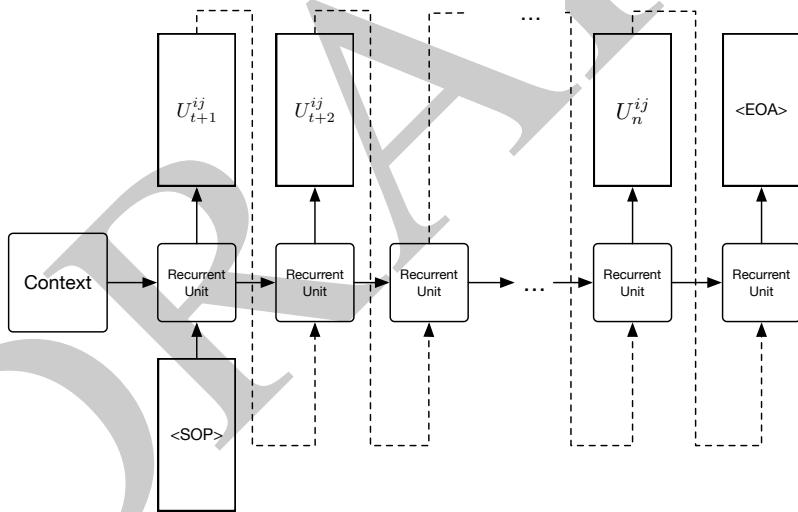


Figure 3.4: Context decoder of Action Path Model. In the decoder, a prediction mark "<SOP>" is used to initiate decoding process, and an ending mark "<EOA>" as a sign to terminate decode process. The output of decoder uses a softmax intermediate operation to magnify and normalize the probability of predicted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

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

3.3.3 Recurrent Unit

The recurrent unit in the Action Path model is not as standard as original Long Short-term Memory unit (LSTM) [Hochreiter and Schmidhuber, 1997] or Gated Recurrent unit (GRU) [Cho et al.,

2014].

When using LSTM as recurrent unit, we feed time duration ($d_1^{ij}, d_2^{ij}, \dots, d_n^{ij}$) 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:

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

where $t = 1, 2, \dots, n$; $P^{(I)}, Q^{(I)}, P^{(F)}, Q^{(F)}, P^{(O)}, Q^{(O)}$ 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, we feed time duration ($d_1^{ij}, d_2^{ij}, \dots, d_n^{ij}$) in to update gate Z_t , and others (reset gate R_t , hidden state h_t) stay the same:

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

where $t = 1, 2, \dots, n$; $P^{(Z)}, Q^{(Z)}, P^{(R)}, Q^{(R)}, P^{(H)}, Q^{(H)}$ 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 completely different than introduce 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.

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 than other marks, since in practice, "<EOA>" is represented in different symbols of categorical clickstream, which as a label to involve classification of user actions.

Assume action paths are labeled by ont-hot encoded ending marks $EOA_1, EOA_2, \dots, EOA_m$ and the last output of decoder hidden state is h_n , we have:

$$\begin{aligned} \hat{y} &= \text{argmax}(\text{softmax}(W^{(M)}h_n)) \\ \hat{y} &\in \{EOA_1, EOA_2, \dots, EOA_m\} \end{aligned} \quad (6)$$

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) is used to select labels with highest probability, scilicet, argmax selects predicted pages with 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 to our scenario.

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

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

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 pages and eliminate the rest of pages from evaluation, and finally selects k best clickstreams. The pseudocode is given in Algorithm 1.

Algorithm 1: Output Clickstream Search

```

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

```

Remark. The algorithm produces an heuristic output with given clickstream context. Combining with *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 advertisement page is far from a desired page if embeddings are learned correctly.

4 Experiment

The following of this chapter, we rationalize the process of our lab study then 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-Maximilians-Universitaet Muenchen. Data was collected from the mainstream browser Google Chrome on a self provided desktop computer and a laptop.

In lab study, we select three mainstream websites, Amazon/Medium/Dribbble that covers categories for shopping, media consuming and design brainstorming. Then we manually designed 9 reasonable (discuss in section 4.3) context-given browsing tasks (three for each website) to simulate three different browsing behavior. Each task requires participant start from a starting page of a given website, and all tasks do not restrict participants use the given website, but also allow them access websites outside the landing page to help them complete the task. Participants start browsing after they completely understand the requirements of each task, and no interruption or question answering during the task except exceeding time limit of a task, however subjects can either acquire more time to accomplish the task or give up directly.

The study is designed as a within-subject study, thus every participant performs all tasks. To eliminate the learning effect due to the long time of using same websites, we use Latin square [Cochran and Cox, 1950] for the device and tasks participation order to our participants.

21 participants with a mean age of 23.04 (standard deviation of 3.216, min=18 and max=19) took part in the study, 10 male and 11 female, whom are recruit anonymously and randomly via a mailing list.

4.1 Environment

The lab study uses two self provided devices: a desktop computer and a mobile laptop. The reason of choose two morphology of computing device is our study requires recording a complete clickstream of during the study.

A major issue of mobile devices is the operating system installed in mobile phone does not open the permission to allow us to collect data precisely over pages. Though Android device can overpass system permission to privilege, the user behavior between iOS and Android device is still completely different with different models. Subjects shows abnormal behavior when they use a newly provided device. Therefore we stick our study environment to desktop devices, which empower us easily collects the clickstream data from plugin-supported browsers.

Although all modern browsers support plugin development, however considering the usage share of all browsers on the market, Google Chrome obtains 61.7% market shares of desktop browsers, and Apple Safari only shares 15.0% of the market [StatCounter, 2018]. Clearly, Google Chrome dominant the desktop web browser.

Therefore, we decide to use Chrome to establish our plugin of data collection. The questionnaire after our lab study indicates the browsers usage share of all subjects, as shown in Table 4.1, which further supports our decision of 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 reason of our context-given browsing task, we first present and discusses the common three types of daily browsing behavior: goal-oriented, exploring and fuzzy.

These three terminologies are aggregated from behaviors that discussed in former qualitative researches, all these terminologies are based a fundamental theory of interdisciplinary perspective information seeking behavior [Wilson, 1997] as we discussed in Chapter 2.2. Table 4.2 compares the differences between former research and ours.

Table 4.2: Terminologies 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

Goal-oriented behavior A user opens a browser caused by a determined purpose for business work, communication, school study, literature research and etc. For instance, a college student has a goal of downloading latest lecture slide, the student then access college website and navigates to the lecture homepage. Finally, the student exit browsing after download the slides.

Exploring behavior A user opens a browser aimlessly, the person explores and consumes the content on the Web. For instance, a person who accesses an utility web application, he/she explores what functions are provided and what he/she can do while using the application.

Fuzzy behavior A user opens a browser with a fuzzy expectation, the clearness of the access purpose is in between of goal-oriented behavior and exploring behavior. For instance, a researcher heared a new technique proposed in other field that may influence he/she's study, then the person opens a search engine to seek existing follow up researches.

4.3 Tasks Design

We designed 35 browsing tasks, after conduct a pilot study, 9 tasks are selected for three websites: Amazon.com, Medium.com and Dribbble.com because of the following reasons:

1. These three websites all have coresponding tasks to the three type of browsing behavior;
2. Each of the task can be finished around 5 to 10 minutes;
3. All these websites are mainstream websites, they do not require massive professional domain knowledge for using.

Moreover, the unselected tasks are listed in Appendix B.3.

4.3.1 Goal-oriented Task

We designed and selected an appropriate goal-oriented task for selected websites respectively, and each task is designed with three determined goal.

- **Amazon.com:** *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.*

This task contains three determined purpose since a subject is required to add three items to the cart. There are few hidden consideration behind the task, which makes the task more realistic: a) There is a budget of this task, which requires subjects must consider the price of items instead of simply add the first recommended item to cart; b) the starting page is amazon.com instead of amazon.de. This decision requires subjects must also consider the currency rate between US dollars and Euros for budget. c) There are some items cannot be shipped to Germany (the study took place in Germany). As a result, subjects cannot add these items to cart and they should find other alternatives.

- **Medium.com:** *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.*

This task contains three determined purpose since there are three fixed traveling destination. The task also implies few considerations that increase the required interaction of the task to subjects: a) The website only offers English version, some Japanese character may appear in an article, thus, a translation util may be used while the study; b) An article may appears numerous noun, such as toponym. Search engine may used while the study; c) the articles, those require a membership to unlock reading, cannot be elevated.

- **Dribbble.com:** *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.*

The task also has three determined purpose since subjects are quired to download three candicate trademarks. While the participation, subjects still need take few implicit facts in to account: a) Subjects who unfamiliar with the term "Cloud Computing" need visit other explainations to figure out the vision and mission of this type of company, and subjects whom already familiar with the term still need to compares the designed made by other competitors. b) Subjects should aware some of the designs shared on the website are not suitable for trademark or icon design.

4.3.2 Exploring Task

Exploring tasks simply do not provides any deterministic objective, and all websites has a designed exploring task for subjects.

- **Amazon.com:** *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.*

Although the task do not require any specific items to the subjects, the task remains three different purpose because participants need add three items to the cart. This designed task is aimlessly because: all tasks is not formerly informed to participants, they either do not have needs of buying items or formerly exist needs of buying a specific category but do not have a product candicate yet. Besides, the description of the task ask participants start from a product category, which avoids goal-oriented buying a specific product.

- **Medium.com:** *Visit a category you are interested in and elevate three post you like.*

Similar reason as discussed in Amazon.com's exploring task. It is well to be reminded that Medium is a media website, visiting a specific article formerly read before participation is

relatively difficult since all contents showed to users are daily updated. Thus the task can be directly consider as an exploring task.

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

Dribbble illustrates designs by using image gallery. The major difference between Dribbble and Google Image Search is dribbble is a user-centered content aggregation website, but Google Image Search is a simple content aggregation engine. As a result, there will be two different interaction in Dribbble: exploring designs based on keywords and categories, or exploring designs based on users. The latter can helps its user finding similar designing style. The task is aimlessly since the task simply describes nothing and completely let participants explore their preferences.

4.3.3 Fuzzy Task

Each of our selected websites also has an fuzzy task respectively, and there are three major goals per task.

- **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 clearness of the task is stronger than exploring task but weaker than goal-oriented task, because The task restricts participants adding items for a specific purpose (birthday present) but not points any specific product.

- **Medium.com:** *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.*

The clearness of the task is stronger than exploring task, because it asks a participant to exploring a non-deterministic direction of looking for secondary cities. But the clearness of the task is weaker than goal-oriented task due to secondary cities described in Medium's user posts is unclear, participants suppose to make decision themselves. Furthermore, this ask is asking regarding traveling China around a week. Cities cannot be randomly selected because to make traveling plan requires consider geographic location of the city.

- **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 purpose of downloading images of animals, which restrict participant to a specific direction, thus, the clearness of the task is stronger than exploring task. However, the task describes a scenario of using these images in a presentation, and hence participants must consider continuity of design style, which makes the clearness of the task is weaker than goal-oriented task.

5 Evaluation

In this chapter, we conduct evaluations to 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 an URL as a step of clickstream if a participant uses back button rollback to a previous visited page without requesting server. A clickstream also has a subjective difficulty score from 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.

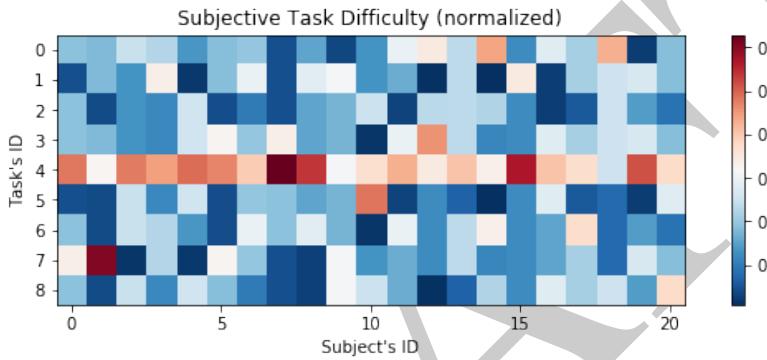


Figure 5.1: Subjective difficulty score: each column indicates an individual subject and each row indicates a browsing task. Tasks from 0 to 8 represent Amazon Goal Oriented Task, Amazon Fuzzy Task, Amazon Exploring Task; Medium Goal Oriented Task, Medium Fuzzy Task, Medium Exploring Task, Dribbble Goal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

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

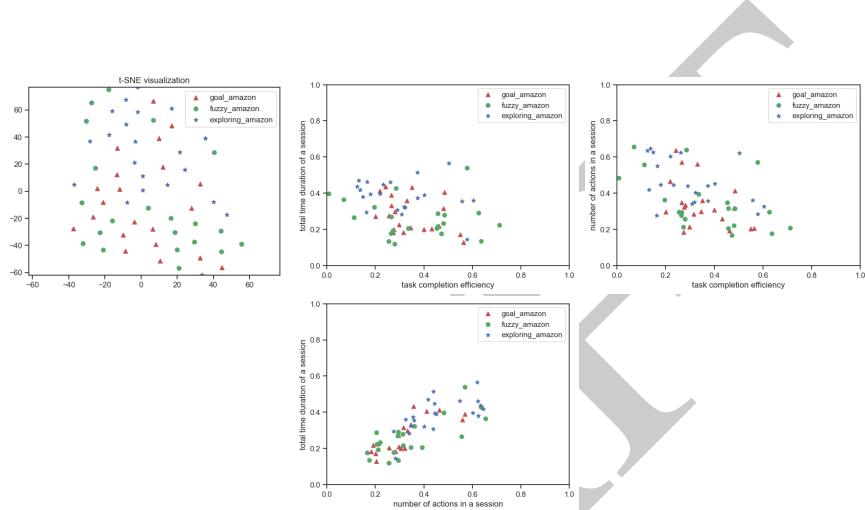


Figure 5.2: TODO:

TODO: table of classification report

more U-test, feature importance.

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 time 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 tasks.

Our training parameters are: The GRU latent dimension is 10, training process feeds 151 clickstreams and propagates 500 epochs with batch size of 32. In the end of training, we use Adam optimizer, evaluate on 38 clickstreams and achieved 100% accuracy on our validation set.

The validation loss during the training is as shown in Figure 5.3.

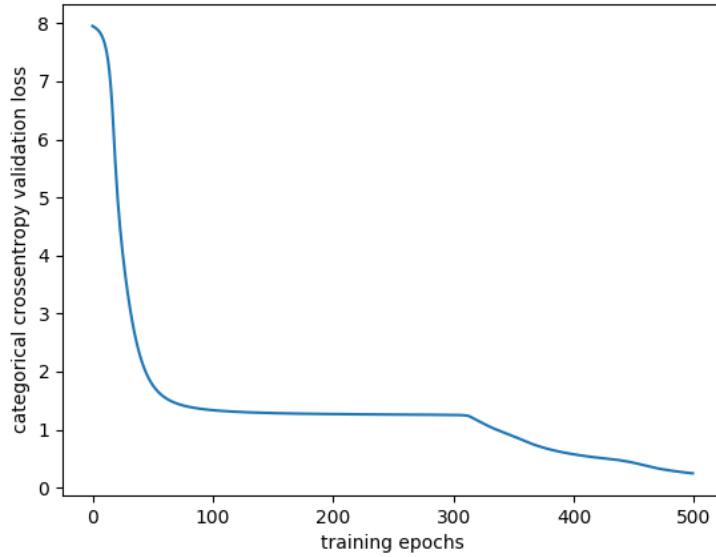


Figure 5.3: Categorical Cross-Entropy Validation loss curve while 500 epoches. The curves indicates the training process is not an overfitting since the loss is not increasing.

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 performance (100% of three class classification in this dataset) when we have more data.

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 visit actions as well as completion effeciency and etc. 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 to classify more precise categories of browsing behavior, perform a future investigation may be significance.

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 ?? illustrates the best accuracy we archieved for when use different split ratio.

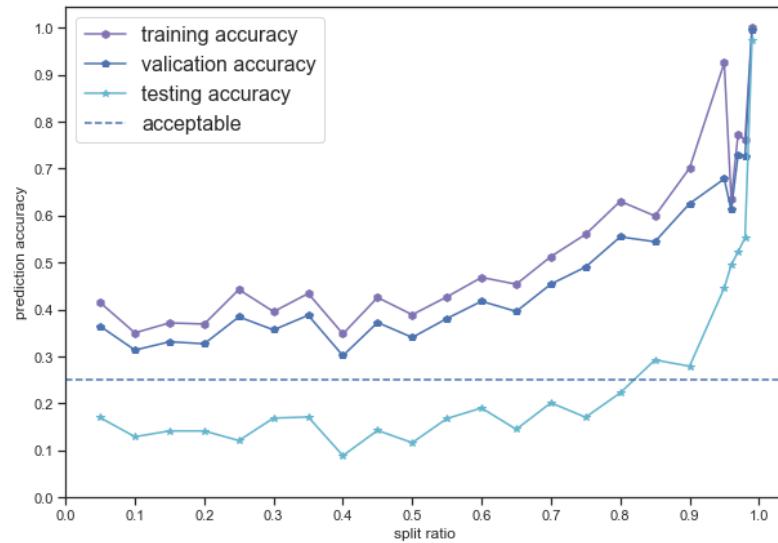


Figure 5.4: TODO:

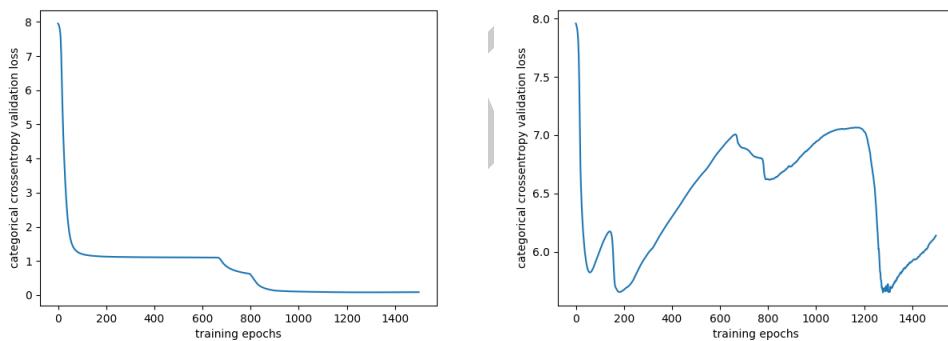
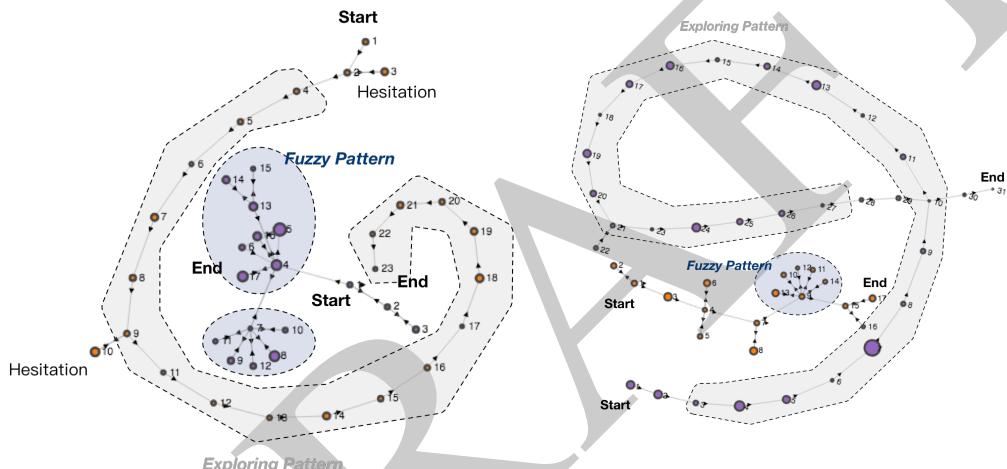
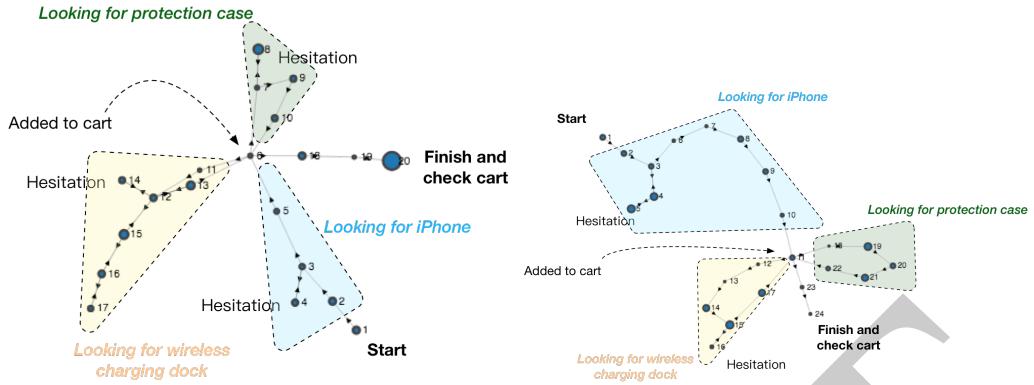


Figure 5.5: TODO:

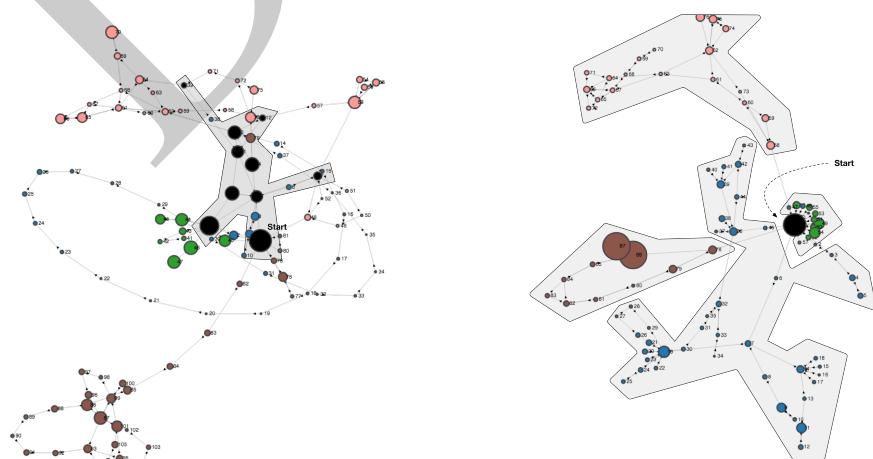
5.4 Action Path Visualization

This section visualizes the actual action path of users and discusses the behavior qualitatively. Note that we collected 189 clickstream in total, which is not possible to illustrate all of them in the thesis, we selected three typical clickstreams to discuss and provided a visualization tool to help readers to explore them.

5.4.1 Individual Common Patterns



5.4.2 Cross-user Overlap Patterns



DRAFT

6 Applications

This chapter we first introduces a possible application of our proposed model and how it could benefit user, the proposed design of the application including frontend, backend architecture as well as database that mostly suitable for the data collection. Then we formalize and discusse the possibility and benefits as a standard Web API for developers.

6.1 Client Side Browser Plugin

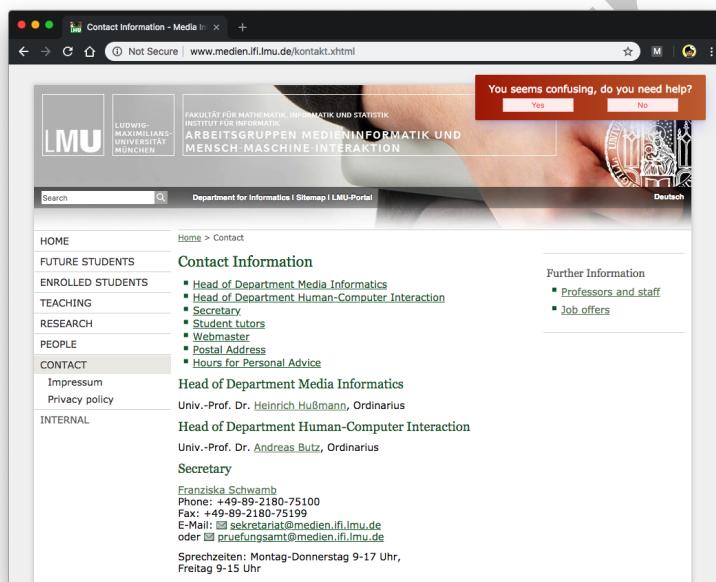


Figure 6.1: TODO:

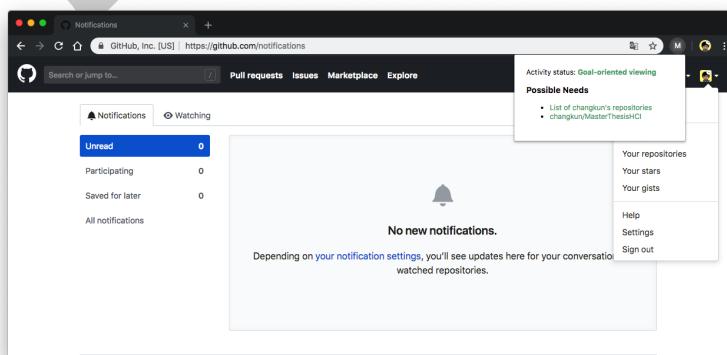


Figure 6.2: TODO:

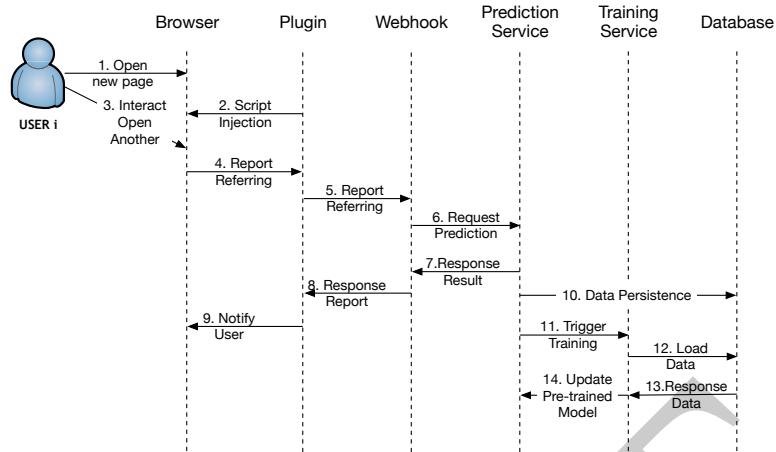


Figure 6.3: TODO:

6.2 Standard Browser Web APIs

Web APIs is a generic term used in various fields of development. Web APIs in a context of web browsers mainly indicates the APIs provided by browser manufacturers to developers that helps web application can even close to manipulate hardwares, for instance, WebAssembly [W3C, 2018].

Nowadays, there are experimental standard Web APIs integrates complex features to web developers, e.g. Web Speech APIs [Shires, Glen and Jaegenstedt, Philip, 2018], and only Google Chrome (after version 24) supports. The specification proposal was initiated by Google and according to the source code of Chromium, the APIs are implemented based on the speech recognition service provided by Google Cloud Platform ¹.

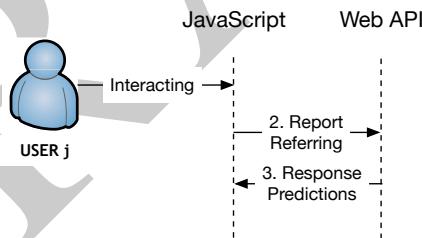


Figure 6.4: TODO:

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

7 Discussion

8 Conclusions

8.1 Summary

This thesis explored an action path model that describes client-side user clickstream. To justify our model, we designed nine browsing tasks for three browsing behavior and held a user study that simulates these behavior. Then 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 overlapping patterns among client-side clickstream. As an application show case, we illustrated a browser plugin that monitors client-side user clickstream to predicting future movements of web browsing and discussed the benifits of this plugin. Futhermore, 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 findings are generic and subservience. The model can not only be use on desktop but also can be implemented in a mobilephone, 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 their product user experience.

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.

DRAFT

Appendix

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

- Thesis homepage: <https://changkun.us/thesis/>;
- GitHub repository: <https://github.com/changkun/MasterThesisHCI/>.

All related text, picture and video content are licensed under a Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License². The other parts of the thesis (such as program source code) are licensed under a MIT Public License³.

A Content of enclosed USB

1. /documents/ - TODO

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 task⁴.

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<http://creativecommons.org/licenses/by-nc-sa/4.0/>

³<https://github.com/changkun/MasterThesisHCI/blob/master/LICENSE>

⁴The order of the tasks are rearranged through Latin square, this section only illustrate one possible order of tasks

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

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 February. Looking for the entrance to register the examination. You must keep seeking and stop when you selected the first track of February 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 entrance 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 malfunctioning 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: 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

Bibliography

References

- [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.
- [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 click-stream data analysis framework for understanding web users' information behavior. *iConference 2017 Proceedings*.
- [Cho et al., 2014] Cho, K., van Merriënboer, B., Gülcühre, 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.
- [Friedman, Wayne and Weaver, Jane, 1995] Friedman, Wayne and Weaver, Jane (1995). Calculating cyberspace: tracking “clickstreams.”.
- [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.
- [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 search-streams: 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.
- [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.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 & 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.
- [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.
- [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.
- [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.