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Masterarbeit

Understanding and Predicting *Client-side* User Clickstream

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Aufgabenstellung

Problem Statement Under standing user behavior helps designer optimize their product user experiences. Meanwhile, users can benefit more productive from it. Since user intents are elusive, changeable and sometimes even undetermined, predict their behavior usually difficult and impoissible. In most cases, a user may performs a series of wasted actions before reach an intent destination. Nevertheless, user intents becomes clear step by step after performs a series of actions in a given context.

Scope of the Thesis To tackle the aforementioned challenges, the objective of this thesis is to develop a system that tracking user actions within a website, As a first step, literature review ... Based on the literature review, a intent model should be developed ... Then a system should implements the ... Nevertheless, user intents becomes clear step by step after performs a series of actions in a given context.

Tasks conduct a literature review to identify research questions regarding clickstream research,

Requirements asdfasdf

Keywords Clickstream, User Behavior, Sequence Learning, Information Seeking Behavior

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 11, 2019 . . . .

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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, and we call it Action Path model. To justify our model, we first established a lab study and collected clickstream data of individuals, consists of chronologic URLs and corresponding stay durations of each URL, with manually designed nine different web browsing task for three mainstream websites based on the theory of information behavior. Each website has three types of tasks, including goal-oriented, fuzzy and exploring browsing task, which characterized the corresponding three browsing behaviors. 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 client-side 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, our quantitative analysis indicates that goal-oriented, fuzzy and exploring browsing behaviors are almost 100% classifiable based on chronologic URLs, and the prediction performance of our model suggests higher than 60% of accuracy for 3-5 steps of future clickstream prediction. Meanwhile, our qualitative analysis to the clickstream indicates 5 observed patterns, including “ring”,“star”, “overlap”, “hesitation” and “cluster” patterns, which represents the patterns of client-side clickstream. As an illustration of application, we also developed a browser plugin that proactively serves users, as well as suggesting predictions of the possible future clicks to a user. 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 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 clickstream.

Contents

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, bussiness man agilely responses to the concept and immediately initate commercial tracking of their customer to improving marketing affects [Novick, Bob, 1995], customer service and precise advertisment [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 surves 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, 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 exitsting 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 summaried 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 effeciency 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

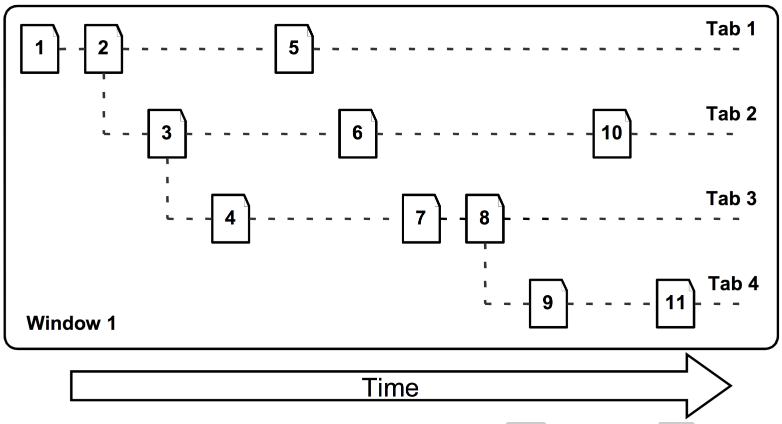


Figure 2.1: Parallel browsing behavior: branching phenomenon [Huang and White, 2010]

Huang et al. [Huang et al., 2012] also discovered the behavior of backtracking browsing however the branching

2.2 Theory of Information Seeking Behavior

This thesis also relevants to information behavior theory. Theory of human information behavior

2.3 Theory of Sequence to Sequence Learning

3 Action Path Models

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 recurrent nerual 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 containing 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 an simplified version of action path that compares vanilla clickstream.

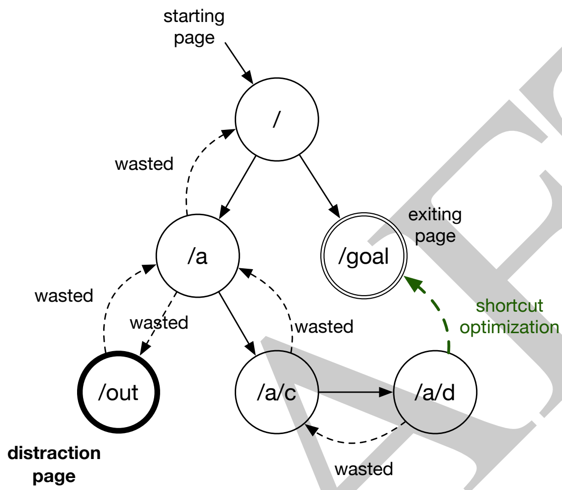


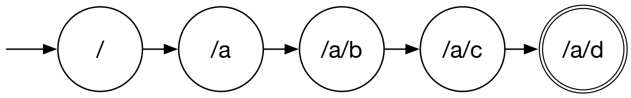
Figure 3.1: A simple action path. A user starts from the starting page, and performed a series of page click actions, ends on a exiting page. The server side records clickstream in the following order: / → /a → /out → /a/c → /a/d → /goal. However the actual user actions are: / → /a → /out → /a → /a/c → /a/d → /a/c → /a → / → /goal. The records on server side lost 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 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 actions is / → /a → /a/c → /a/d → /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.

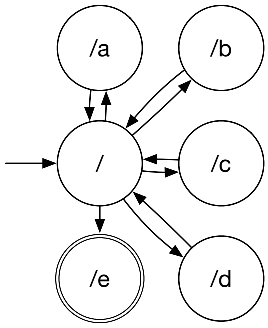
3.1 Completion Effeciency

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 swtich, 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 effeciency* based on shortest path from starting page to exiting page, and stay duration of the action path.



(a)



(b)

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 stady 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 effeciency* E is defined as follows Equation 1:

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

where w_1, w_2 are hyperparameters to balancing the importance of action path and stay duration. According to the duscussion 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 effeciency 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 shortest-path 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.

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

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 $\mathrm{URL}_1, \mathrm{URL}_2, ..., \mathrm{URL}_T$, the objective of url2vec is to maximize the average log softmax probability:

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

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

Remark 1 This model described by Equation 2 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 2 is impractical due to $\nabla \log p(\mathrm{URL}_{t+i}|\mathrm{URL}_t)$ is large because of expnential items, two numerical optimizations based on Hofmann Tree and Negative Sampling are proposed by Mikolv et al. [Mikolov et al., 2013b].

Remark 3 The probability can also be interpret in Bayesian perspective, which provides a 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 an one-hot encoded vector input to the embedding neural network, the item can be treat 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

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 interating the activation function Equation 3:

$$
o_t = W_{oh}\sigma\left(W_{hi}i_t + W_{hh}i_{t-1}\right), t = 1, 2, ..., T \tag{3}
$$

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 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 constrains 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'. Our model convey similar idea from it.

An *action path* from user i in session j consist of a sequence of *url2vec* embedded vectors $(U_1^{ij}, U_2^{ij}, ..., U_n^{ij})$ 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 model consist a context encoder and a context decoder.

3.3.1 Context Encoder

Context encoder encodes URLs one by one and produces a context tensor that encodes the historical user actions, as 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.

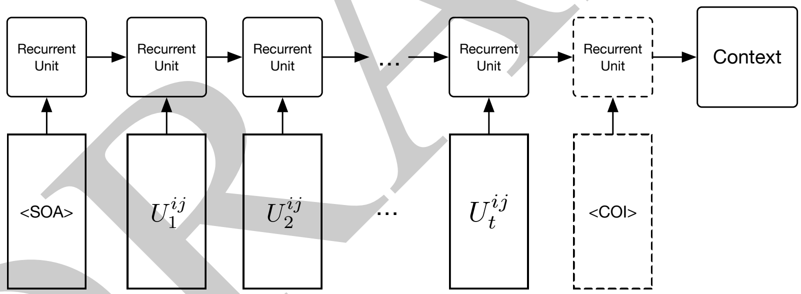


Figure 3.3: Context encoder of Action Path Model. In the encoder, a starting mark "<SOA>" is used as a sign of start feeding URLs, and a trigger mark "<COI>" as a sign to trigger decoder to decodes encoded context tensor. The trigger mark is automatically inserted after the *k*-th URL in the end of encoder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

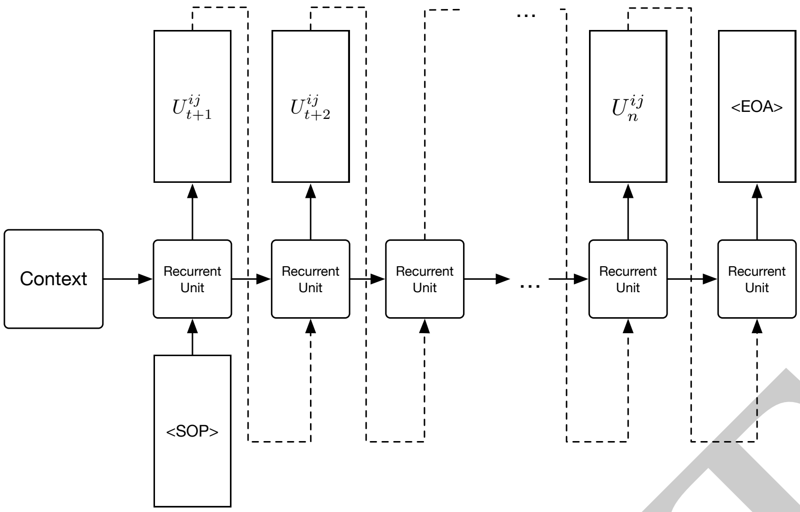


Figure 3.4: Context decoder of Action Path Model. In the decoder, a prediction mark “<SOP>” is used to initiate decoding process, and an ending mark “<EOA>” as a sign to terminate decode process. The output of decoder uses a softmax intermediate operation to magnify and normalize the probability of predicted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

Note that the decoder model in training phase and prediction phase is different. In the training phase, teacher forcing strategy [Williams and Zipser, 1989] is used, the strategy supplys 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].

The original LSTM recurrent unit 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 simplyfies the structure of LSTM into a update gate and a reset gate.

In our recurrent unit, when using LSTM as recurrent unit base, we also 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:

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

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 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 than a simple constant bias in the original 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 7.

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 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) is used to select labels with highest probability, scilicet, argmax selects predicted URLs 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 senario.

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, i.e. we need to solve an optimization problem

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

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 $(o_1, o_2, \dots, o_m)$,
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
    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

In this chapter, we rationalize the process of our lab study based on the theory of human information behavior, then construe the purpose of context given web browsing tasks to 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. Client-side user clickstream data was collected by a embedded collector plugin installed in the mainstream browser, i.e. 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 with design reasons (discuss later in Section 4.3). Then we manually designed 35 reasonable tasks and finally selected 9 context-given browsing tasks (three for each website, discuss in Section 4.3) to simulate three different proposed browsing behavior, namely goal-oriented/fuzzy/exploring behaviors. 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 they access websites outside the landing page to help they complete the task (explicitly informed to participants before participation). 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 (Desktop/Laptop) and tasks participation order to our participants.

Our lab study obtained 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 authorize the permission of allowance to collect data precisely over pages or user actions. Though Android device can overpass system permission to privilge, the user behavior between iOS and Android device is still completely different with different models (TODO: cite support). 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 browsers with plugin supports.

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

Hence, we decide to use Chrome to establish our plugin of data collection. The quesionaire 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 foundation theory and design reason of our context-given browsing task, we first present and discusses three common types of user browsing behavior: **goal-oriented**, **exploring** and **fuzzy**.

These three terminologies are aggregated and incorporated from behaviors that concluded in former qualitative researches, all these terminologies are based on a fundmental theory of inter-disciplinary perspective information seeking behavior and human information behavior [Wilson, 1997] as we discussed in Section 2.2. TODO: 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**

As justification, we combines Ellis' Model and "information use" behavior proposed in information behavior theory to justify our summarized behaviors:

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

Goal-oriented behavior indicates an actively information seeking 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". Under browsing behavior, a determined "information use" can be observed or 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 etc.

Exploring browsing behavior indicates a complete opposite behavior comparing to goal-oriented borwsing behavior. More formally describing exploring behavior using Ellis' model, 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*), he/she explores what functions are provided one by one and what he/she can do while using the application (*chaining* and *browsing*).

Fuzzy behavior occurs when a user initiate visiting session for information use with non-systematic, incomplete prior knowledge that may browsing ongoing for updating the framework of knowledge until final acquisition or abandon.

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

For instance, a researcher heared a new technique proposed in another scientific field that may influence he/she's research, then the person opens a search engine (*starting* and *chaining*) to seek (*browsing*) existing (*differentiating*) follow up researches (*monitoring*). The browsing may ends without information use because of the technique is irrelevant to he/she's research.

Remark Table 4.3 illustrates a mapping from these three browsing behavior to the complete human information behavior. Note that "information needs" is not suggested in T. Wilson's theory since "information needs" is not

Table 4.3: 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**

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 apears 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 prupose 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 remined 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 questionaire (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.

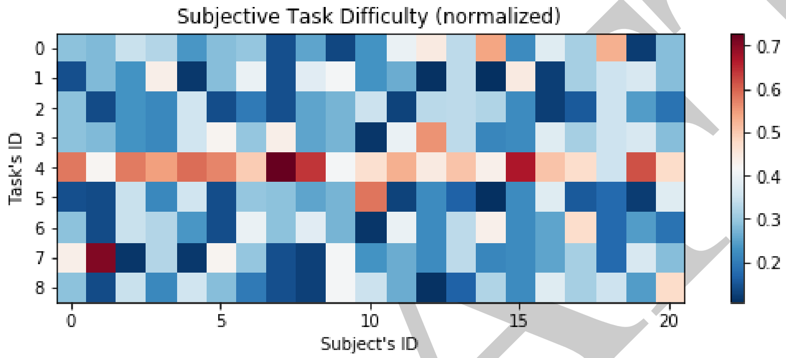


Figure 5.1: Subjective difficulty score: each column indicates an individual subject and each row indicates a browsing task. Tasks from 0 to 8 represent Amazon Goal Oriented Task, Amazon Fuzzy Task, Amazon Exploring Task; Medium Goal Oriented Task, Medium Fuzzy Task, Medium Exploring Task, Dribbble Goal 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

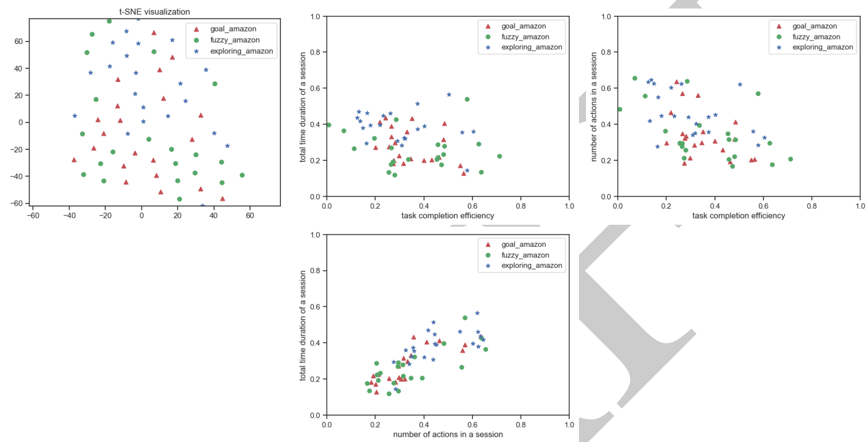


Figure 5.2: TODO:

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 archieved 100% accuracy on our validation set.

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

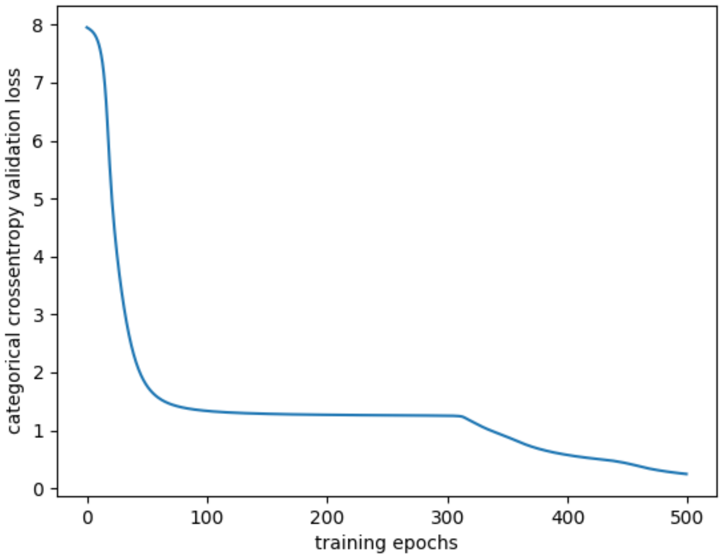


Figure 5.3: Categorical Cross-Entropy Validation loss curve while 500 epoches. The curves indicates the training process is not an overfitting since the loss is not increasing.

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.

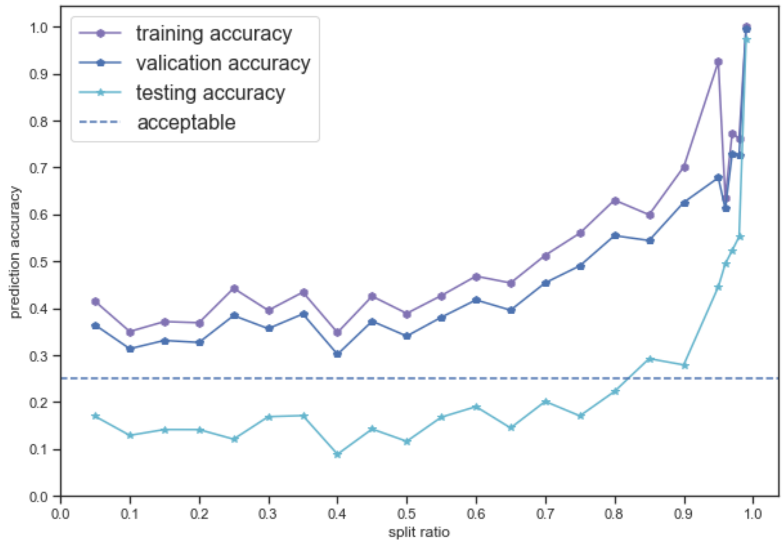


Figure 5.4: TODO:

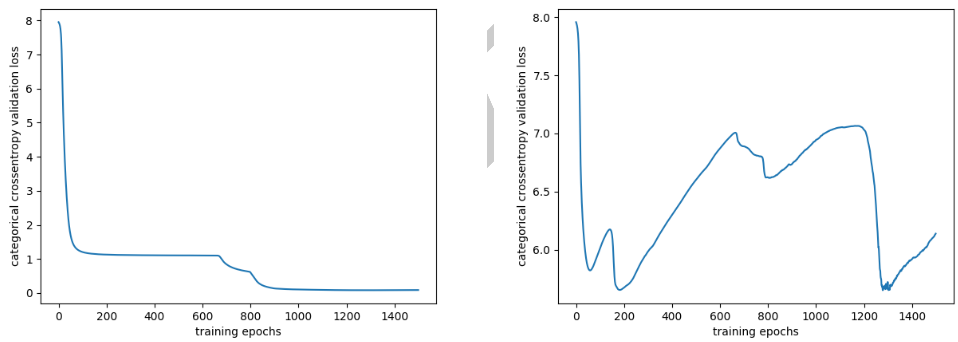


Figure 5.5: TODO:

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

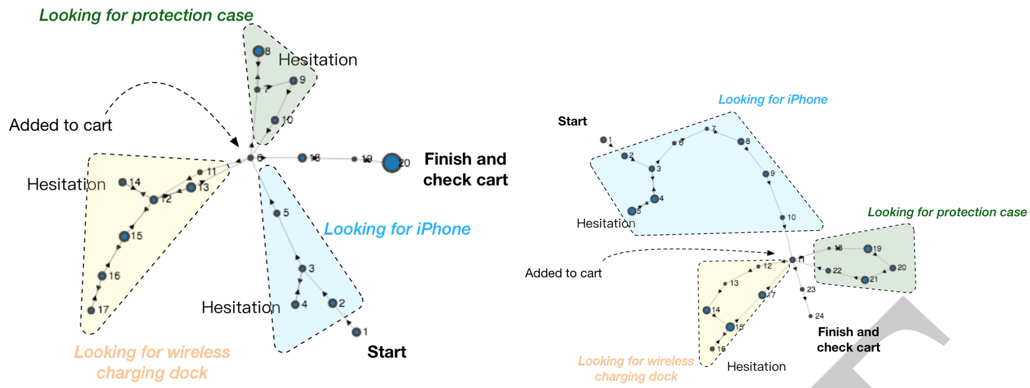


Figure 5.6: TODO:

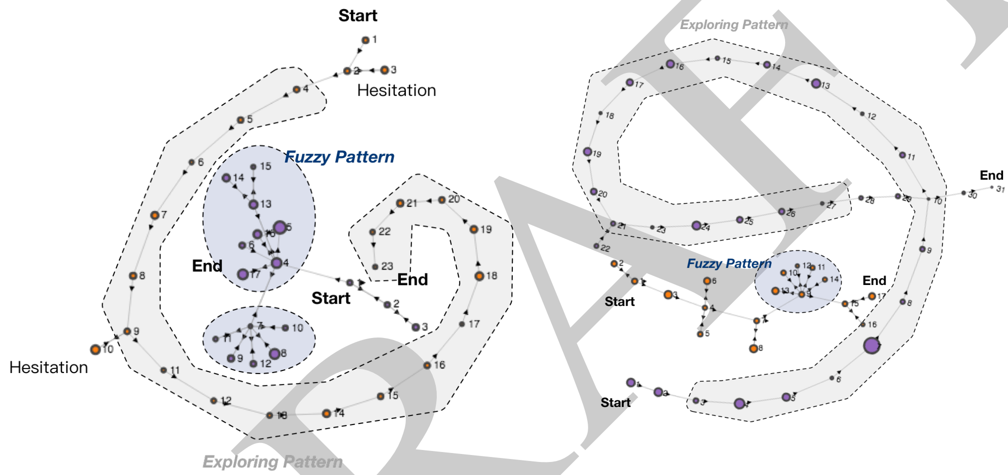


Figure 5.7: TODO:

5.4.2 Cross-user Overlap Patterns

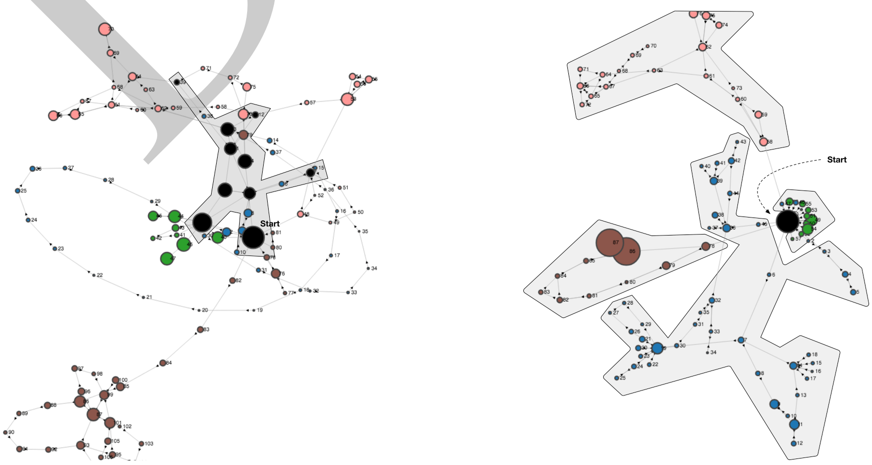


Figure 5.8: TODO:

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 discuss the possibility and benefits as a standard Web API for developers.

6.1 Client Side Browser Plugin

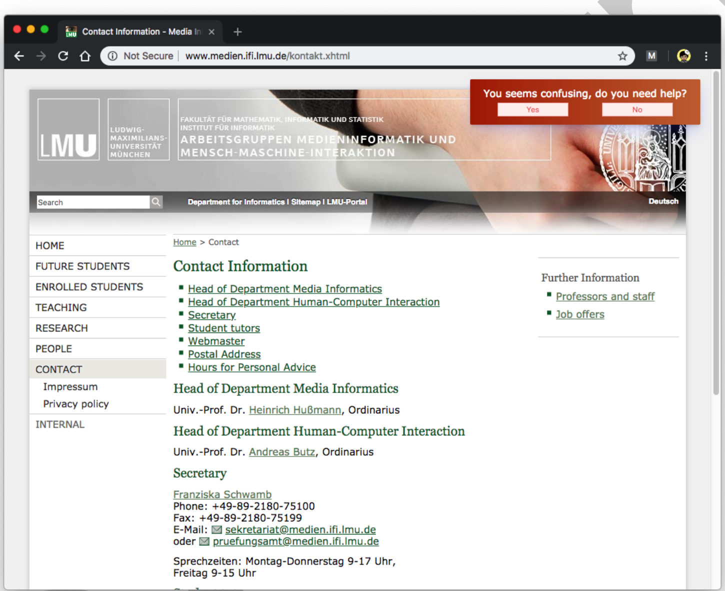


Figure 6.1: TODO:

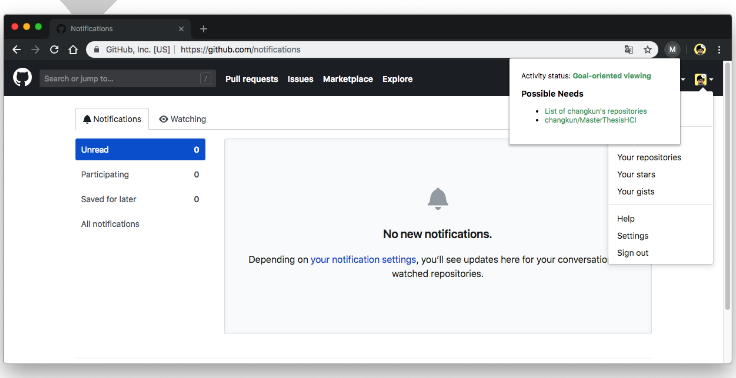


Figure 6.2: TODO:

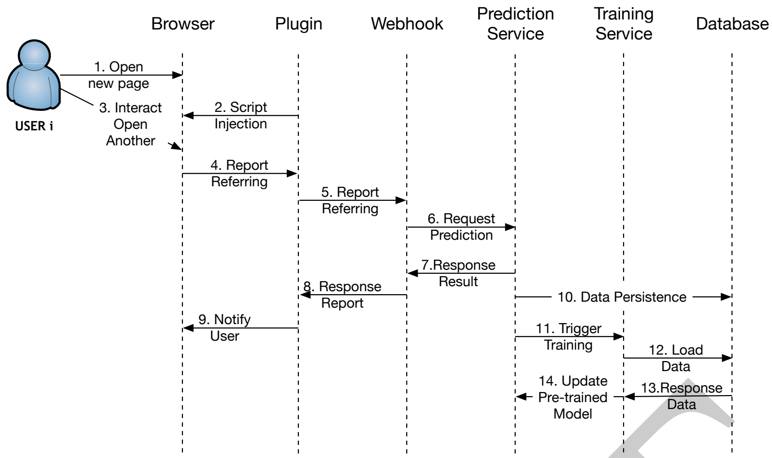


Figure 6.3: TODO:

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 manufactures 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].

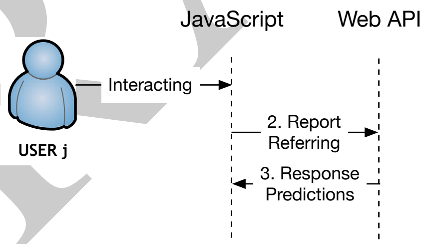


Figure 6.4: TODO:

[1] `https://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 proposed an action path model that describes client-side user clickstream. 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 show case, we illustrated a browser plugin that monitors client-side user clickstream to predict 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 finding indicates the completion difficulty in different type of tasks are significant different, especially the difficulty of fuzzy task is significant difficult than goal-oriented task, and the goal-oriented task is also significant difficult than exploring task. For completion efficiency, length of client-side clickstream and total duration of the clickstream

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.

Appendix

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

- 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[2]. The other parts of the thesis (such as program source code) are licensed under a MIT Public License [3].

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 task [4].

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
[4] The 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 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: 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

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