Study Navigator: An Algorithmically Generated Aid for Learning from Electronic Textbooks*

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We present *study navigator*, an algorithmically-generated aid for enhancing the experience of studying from electronic textbooks. The study navigator for a section of the book consists of helpful *concept references* for understanding this section. Each concept reference is a pair consisting of a concept phrase explained elsewhere and the link to the section in which it has been explained. We propose a novel reader model for textbooks and an algorithm for generating the study navigator based on this model. We also present an extension of the study navigator specialized to accommodate the information processing preference of the student. Specifically, this specialization allows a student to control the balance between references to sections that help refresh material already studied vs. sections that provide more advanced information. We also present two user studies that demonstrate the efficacy of the proposed system across textbooks on different subjects from different grades.

1 Introduction

With the emergence of abundant online content, cloud computing, and electronic reading devices, the multi-billion dollar textbook industry is poised for transformative changes. Notwithstanding understandable misgivings (e.g. Gutenberg Elegies (Birkerts, 2006)), textbooks cannot escape what Walter Ong calls "the technologizing of the word" (Ong, 1982). Already, there are initiatives such as "no child left offline" that are centered around the availability of electronic textbooks for achieving the goal of "any time, any place, any pace" learning (CDE, 2012). There are ongoing efforts to create high quality free, open electronic textbooks (CK-12,). A recent study estimated that 29% of adults in USA own tablet computers or eReaders compared to 2% less than three years ago (Meeker, 2012). These trends are not limited to USA or other developed nations alone. For example, the Government of India is said to be developing a low cost tablet,

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Aakash, pre-loaded with educational content for distributing to millions of students (IMHRD, 2012).

We believe electronic textbooks provide huge opportunity to invent new tools and techniques to facilitate effective use of this medium. Some of the new functionalities that can be enabled in future textbooks include:

- *New navigations*: The book can infer navigational aids beyond table of contents, back-of-the-book index, and simple hyperlinks.
- *Adaptability*: The book can be personalized to suit the student's knowledge of the subject material as well as learning styles. The presentation can be dynamically modified to adapt to the requirements of the student based on prior interaction with the book.
- *Richer experiences*: The book can be augmented with images, picture galleries, videos, and live simulations to provide a better learning experience.
- *Continuous self-assessment*: The book can offer personalized assessments and recourses to help students learn in a non-invasive way.
- *Collaborative learning*: The book can propose interactions with other students appropriate for the part of the book a student is studying. It can also suggest compatible study groups that can span different geographical regions.

This paper presents one particular study aid we have designed specifically for electronic books, called *study navigator*. It is generated algorithmically and accommodates the information processing preference of students. It provides easy access to concepts explained elsewhere in the book that are most relevant for understanding the present section. Refer to the pair consisting of a concept useful for understanding a section and the link to the section where it has been explained as a *concept reference*. The study navigator consists of significant concept references for every section in the book. It can be activated by a student while reading a particular section and shows the corresponding concept references. Only a small number of significant concept references are shown to avoid undue cognition burden on the reader.

Our main technical contribution is the algorithmic mining of the concept references in the context of a reader model we propose for textbooks. Our reader model is inspired by the random web surfer model and personalized PageRank computation (Jeh and Widom, 2003). However, the random walk used in our model has significant differences, such as (1) the preference vector gets updated during certain types of transitions while it is fixed in personalized PageRank computation, and (2) the return transition occurs with a large probability in our model unlike in PageRank computations.

The study navigator can be adapted to match a student's information processing preference. Specifically, we consider two types of readers: *curious* and *diligent*. When reading a section, a curious student might be open to referring unread later sections that provide advanced information while a diligent student might prefer references only to earlier sections to refresh the material the student has already read (Anderson, 1982). We present extension to the reader model to incorporate a student's preference. We call this study navigator the *student-specific navigator*. It allows students to control the balance between sections that help refresh material already studied vs. sections that provide more advanced information by adjusting a curiosity-factor knob.

We also present the results of two user studies for assessing the performance of our study navigator system. The first study did not use the specialization of the study navigator for reader types (and implicitly assumes curious readers). The overall finding of this study was that the judges found the references provided by the study navigator to be quite helpful. Our in-depth failure analysis revealed that in the cases where the judges preferred references other than those provided by the study navigator, it was mostly for sections that reminded them of the material covered earlier. Our second study confirmed the existence of reader types and helped us identify users who were dominantly curious or diligent. Now by providing references generated by the student-specific navigator to the respective types of readers, we found that the respective user types found the corresponding references useful.

The paper proceeds as follows. We begin with a discussion of related work in §2. We present the algorithms for generating the study navigator in §3 and its experimental evaluation in §4. We next describe the student-specific navigator that incorporates reader types and its evaluation in §5. We present conclusions and future directions in §6.

The thrust of this paper is on describing how the study navigator automatically generates concept references for various sections of a given textbook. The manner in which these concept references are surfaced and integrated in the user experience of studying from the electronic book is of paramount importance, but beyond the scope of this paper.

2 Related Work

Authoring tools for adaptive navigation and presentation: A prominent system in this category is InterBook (Brusilovsky et al., 1998), a tool for creating an electronic book that can adapt to users with different backgrounds, prior subject knowledge, and learning goals. The data required to enable this adaptation must be provided as input by the author. We aim to infer the concept references needed for building the study navigator by algorithmically mining the text of the book.

Adaptive educational hypermedia systems: The goal of these systems is to combine hypermedia systems with Intelligent Tutoring Systems to adapt web-based educational material to the needs of particular users (Brusilovsky, 2001). They aim to help educators manually setup personalized courseware based on the cognitive style (*e.g.*, AES-CS (Triantafillou et al., 2004), EDUCE (Kelly, 2008)) or learning style (*e.g.*, ELM-ART (Brusilovsky et al., 1996), ELM-ART II (Weber and Specht, 1997), KBS Hyperbook (Henze and Nejdl, 2001), INSPIRE (Papanikolaou et al., 2003)). They operate under the premise that the underlying information to enable this personalization is available to the person creating the courseware. We, on the other hand, aim to provide automated techniques.

Exploratory hypermedia systems: We put various systems categorized as ASK systems (*e.g.*, Trans-ASK (Bareiss and Osgood, 1993) and ASKTool (Cleary and Bareiss, 1996)) into this category. They aim to provide an interactive environment that mimicks conversing with an expert for its users to be able to find content of interest and/or ask follow-up questions to retrieve additional topics. In contrast, we look at the problem of identifying sections that are needed for understanding the current section.

Text browser and search tools: SuperBook (Remde et al., 1987), ScentIndex (Chi et al., 2006), ScentHighlights (Chi et al., 2005), and Smart (Salton et al., 1994) are examples of such systems.

In contrast to our system, these systems do not provide references to concepts/sections that are useful for understanding a given section.

Back-of-the-book indices: While related, there are fundamental differences between a back-of-the-book index (Mulvany, 2005) and what we call concept references associated with each section of the book. In principle, one could do a sort on section numbers of a back-of-the-book index and thus find the important phrases present in each section. But it solves only half of the problem – if we know that a concept phrase φ is important for understanding a given section, we can use this approach to know all the sections where φ is possibly explained. But how do we know which φ is critical for understanding the present section? In fact, it is quite likely that φ might not even appear as a phrase in the present section[1]. For the same reason, hyperlinking some phrases appearing in the current section is not sufficient. Another key difference is that back-of-the-book index generation algorithms compute global significance of concept phrases at the book level without taking into account where in the book the reader currently is or who the reader is.

3 Study Navigator

The study navigator system is designed to make it easy for a student to find concepts described elsewhere in the book that are most relevant to the material discussed in the present section. We refer to the pair consisting of a concept useful for understanding a section and the link to the section where it has been explained as a *concept reference*. For the purposes of this paper, we represent a concept as a phrase, and denote it as *cphr*. Our goal is to determine a few ⟨*cphr*, section⟩ pairs that are most relevant for understanding the current section.

3.1 Algorithmic Intuition

Suppose that the set of *cphrs* contained in a section as well as the relationship between *cphrs* is available. We then need to determine the concept references that are most significant for understanding a given section s. For this purpose, we need a score denoting how significant is the description of a *cphr* c in a different section t for understanding section s. Given the significance scores of every *cphr* in every other section for understanding section s, we can order ⟨*cphr*, section⟩ pairs by their significance scores and include pointers to the top k ⟨*cphr*, section⟩ pairs in the study navigator for section s.

The significance score of a *cphr* in section t for understanding a different section s can be thought of in terms of how likely is the description of this *cphr* in section t to be referred when a reader is trying to understand section s. How do we formalize and quantify this likelihood? We surmise that while reading a book, a reader would refer to more significant *cphrs* more often.

Reader Model: Consider a student who is reading a textbook starting from the first section. When she is reading a section i, she comes across the *cphrs* in the order $c_{i1}, c_{i2}, c_{i3}, \ldots$. When the

[1]For example, consider the section titled "Ex ante and ex post" which is part of the chapter on income determination in a Grade XII Economics textbook. This section explains the differences between the planned (ex ante) and actual (ex post) values of consumption, investment and aggregate demand of final goods in an economy, and the determinants of the ex ante values of these variables. Concept phrases such as 'factor services' and 'factor payments', which are explained elsewhere in the book in the context of the circular flow of income, are important for understanding the current section, but do not even appear as a phrase in this section.

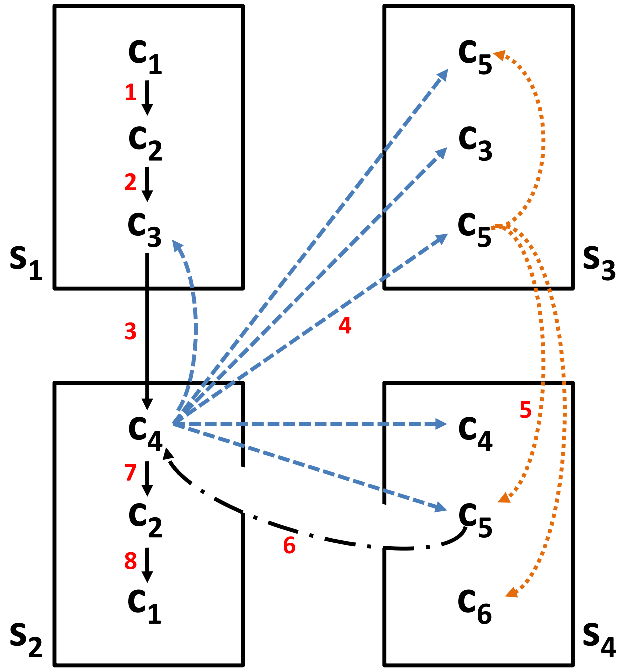


Figure 1: Illustration of Reader Model: Consider a hypothetical textbook consisting of four sections ($s_1, \ldots, s_4$) and six *cphrs* ($c_1, \ldots, c_6$). The reader reads the book starting from s_1. The path followed by the reader is indicated by numbers next to the arrows. Suppose the reader (after reading s_1) does not understand *cphr* c_4 in section s_2, and hence is forced to refer to another section containing c_4 or a *cphr* related to c_4. Let $\{c_3, c_4, c_5\}$ be the set of *cphrs* related to c_4, so that the available digression edges correspond to the edges consisting of dashes. The reader chooses a *cphr* from this set. Suppose she chose c_5. Out of the three occurrences of c_5 in the book, suppose she selected the second occurrence of c_5 in s_3. Thus she follows the digression edge marked 4, to read about c_5 in s_3. After reading about c_5 in s_3, the reader either returns to c_4 in s_2 with a large probability (the return edge not shown) or digresses further. Suppose she digresses further. Let $\{c_5, c_6\}$ be the set of *cphrs* related to c_5, so that the available digression edges correspond to the edges consisting of dots. She selects c_5 from this set and follows the digression edge marked 5 to read about c_5 in s_4. Afterwards, she returns to c_4 in s_2 along the edge marked 6, and persists to read further.

reader comes across a *cphr* c, with a large probability, the reader will be persistent in continuing to read the section. With a certain probability, she may not understand the *cphr* and hence may be forced to refer to another section to seek explanation.

Postulate that whenever the reader does not understand c, she refers to a section containing the same *cphr* c or a different *cphr* related to c. More precisely, the reader picks a *cphr* c' from the set of *cphrs* related to c with equal probability, chooses an occurrence of c' amongst all occurrences of c' in the book with equal probability, and refers to the corresponding section i' to learn more about c'. It is possible that i' is a section earlier than i in the book or it is a later section. After reading about c' in i', the reader has the following options: (a) return to the original section i with a large probability, and continue further reading, or (b) digress further to learn more about c' by referring to a section containing c' or a different *cphr* related to c', that is, pick a *cphr* c'' from the set of *cphrs* related to c' with equal probability and refer to a section i'' that contains c'' amongst all occurrences of c'' with equal probability. In the latter case, the reader

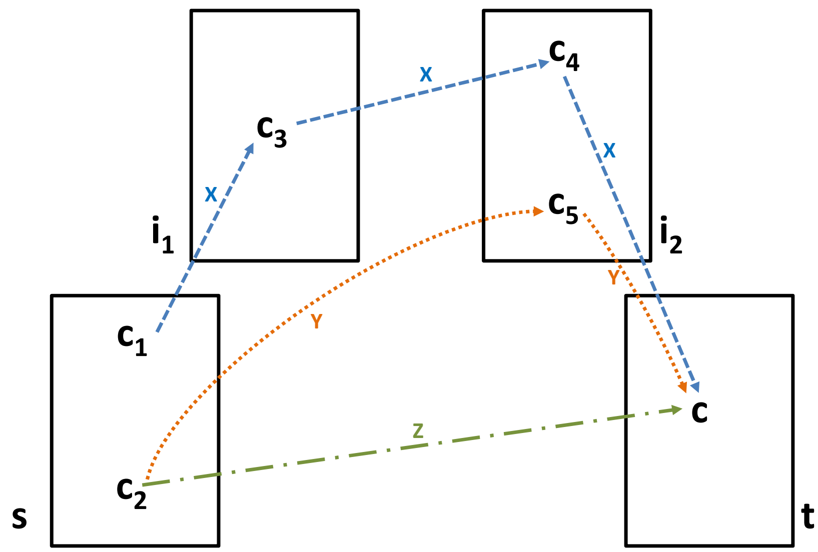


Figure 2: Illustration of how the significance score of *cphr* c in section t for understanding section s is computed: Consider three different readers trying to understand *cphrs* in section s. Reader X is unable to understand *cphr* c_1, and hence digresses to other sections (shown using dashed edges). She may first refer to c_3 in section i_1, followed by c_4 in section i_2, and finally c in section t. Readers Y and Z are unable to understand *cphr* c_2, but digress to different sections. Reader Y refers to c_5 in section i_2, followed by c in section t (shown using dotted edges) while reader Z directly digresses to c in section t (along the edge consisting of dashes and dots). The significance score is obtained by computing the likelihood of each such digression for different readers that reach c in section t starting from section s, and aggregating over many such digressions.

then returns to the original section i, or digresses further. Note that, while digressing, the reader can revisit a section i' (*e.g.*, for reading about c''' which is also explained in section i' and which is related to c''). But the return from a digression is always to the starting section i (irrespective of the number of hops digressed) as the reader is trying to understand section i and the purpose of the digression is to seek better explanation for c occurring in i. See Figure 1 for an illustration.

Computing Significance Scores: Consider different students trying to understand section s. We obtain the significance score of a *cphr* c in section t for understanding section s by computing how often these students refer to the description of this *cphr* in section t when reading section s. More precisely, whenever a reader has difficulty understanding a *cphr* in section s and hence is forced to digress to other sections, we compute how likely is the reader to refer to *cphr* c in section t. We then aggregate these likelihoods over many readers and over all *cphrs* in section s. See Figure 2 for an illustration.

We next formalize the algorithmic intuition presented above, and precisely formulate the reader model and the computation of significance scores.

3.2 Notations

Let $S = \{1, 2, \ldots, n\}$ denote the set of sections in a given textbook. Let C denote the set of *cphrs* (concept phrases) in the book. For each *cphr* $c \in C$, denote the set of *cphrs* related to it by $R(c)$. Note that $R(c)$ includes c. Let $\lambda_s(c, t)$ denote the significance score of *cphr*

S	Set of sections in the textbook ($\|S\| = n$)
C	Set of *cphrs* (concept phrases) in the textbook
$R(c)$	Set of *cphrs* related to *cphr* c
$\lambda_s(c,t)$	Significance score of *cphr* c occurring in a different section t for understanding section s
k_s	Number of desired concept references to be provided in the study navigator for a given section s

Table 1: Notations

c in a different section t for understanding section s. Let k_s denote the number of desired $\langle$*cphr*, section$\rangle$ concept references in the study navigator for section s. Table 1 summarizes key notations.

3.3 Formulation of Reader Model

We formulate the reader model as a random walk over a concept graph $G = (V, E_p \cup E_d)$. Each node $u = \langle i, c_{ij}, j\rangle \in V$ is a $\langle$section, *cphr*, position$\rangle$ triplet corresponding to the occurrence of *cphr* c_{ij} in section i and its sequential position j amongst the *cphrs* in the section. Denote the associated section i by $\bar{i}(u)$ and the associated *cphr* c_{ij} by $\bar{c}(u)$. There are two types of directed edges in G. The set of persistence edges E_p consists of directed edges corresponding to sequential reading of the book, that is, there is a directed edge from $\langle i, c_{ij}, j\rangle$ to $\langle i, c_{i(j+1)}, j+1\rangle$ and from the last concept node in a section to the first concept node in the next section. The set of digression edges E_d consists of directed edges corresponding to forced digression, that is, there is an edge from u to v if $\bar{c}(v) \in R(\bar{c}(u))$ (if *cphr* associated with v is related to *cphr* associated with u).

The random walk consists of three types of transitions:

1. Persistence transition: From any node u, follow the persistence edge, that is, the reader persists to read sequentially from the *cphr* occurrence corresponding to u. Denote the probability associated with such a transition as the persistence factor, α.

2. Digression transition: From any node u, follow a digression edge. Denote the total probability associated with a transition along one of the digression edges outgoing from a node as the digression factor, β. Suppose the reader picks a related *cphr* $c' \in R(\bar{c}(u))$. The reader then selects an occurrence of c' amongst all occurrences with equal probability.

3. Return transition: From any node to which the reader has digressed, return to the node from where the digression originated. This transition corresponds to the reader returning back to the starting point after a digression. Denote the probability associated with such a transition as the diligence factor, γ.

The above walk requires keeping track of sequential position of the reader in the book because whenever the reader has digressed, she needs to return to the position from where the digression originated. In other words, the return transition depends not only on the current state in the walk but also the state from which the reader started the digression. The Markov property can be achieved by creating —V— copies of the nodes (and digression edges) as follows. The modified graph consists of the set V of nodes, the set E_p of persistence edges corresponding to sequential reading, and further, a copy of (V, E_d) rooted at each node $u \in V$. The digressions that originate from any node u are confined to the copy of V rooted at u and the return transitions point to u from all nodes in the copy rooted at u. By creating a separate copy of digression edges for each sequential position (node), we implicitly keep track of the state from which the reader started the digression and thus the return transition can be determined based on just the current state.

3.4 Computing Significance Scores

Consider the random digression walk starting from an arbitrary node u (that is, the walk corresponding to the chain of digressions originating from u consisting of only digression and return transitions but no persistence transitions). In this walk, the return transitions always point to u and the digression transitions are determined based on the current state. Hence, this walk induces a Markov chain over the strongly connected component reachable from node u. This Markov chain is (a) finite (b) *irreducible* since the underlying directed graph for the Markov chain consists of a single strongly connected component [any two arbitrary nodes v_1 and v_2 in this graph are reachable from each other since there are edges from v_1 and v_2 to u and paths from u to v_1 and v_2], and (c) *aperiodic* since self-loops are present at every node in the underlying directed graph for the Markov chain [recall that $R(c)$ includes c, and hence there exists a digression edge from a node to itself]. Thus, the Markov chain satisfies the necessary conditions for applying the fundamental theorem of Markov chains (Motwani and Raghavan, 1995), leading to the claim below.

Claim 3.1 *There is a unique stationary probability distribution $\pi(u, .)$ associated with the random digression walk starting from any node u in G.*

By definition, the stationary probability $\pi(u, v)$ denotes the probability that the walk starting from node u is at node v in the steady state. In other words, this probability corresponds to the relative frequency with which the reader refers the *cphr* $\bar{c}(v)$ corresponding to v when trying to understand the *cphr* corresponding to u and hence larger $\pi(u, v)$ implies that the reader is more likely to refer to v. Thus $\pi(u, v)$ is a measure of the relative significance of an occurrence of *cphr* $\bar{c}(v)$ in section $\bar{i}(v)$ corresponding to v for understanding the *cphr* corresponding to u. Considering the random walks starting from each concept node in a given section s of the book, we can thus compute the significance of a single occurrence of *cphr* $\bar{c}(v)$ in section $\bar{i}(v)$ for understanding *cphrs* in section s. Our goal is to compute the significance of *all* occurrences of a *cphr* in a section. Hence we further aggregate the above score over all occurrences of *cphr* $\bar{c}(v)$ in section $\bar{i}(v)$. In this manner, we also incorporate the frequency of the *cphr* in the section. Note that we chose not to include persistence transitions for significance score computation since sequential reading is the default reading behavior, and we want to take into account the reader's deviation from this behavior in the form of forced digressions.

We thus define the significance score $\lambda_s(c, t)$ of a *cphr* c in section t for understanding section s in terms of the combined stationary probability associated with nodes corresponding to all occurrences of c in t, summed over random walks starting from all concept nodes in section s. We remark that our definition of $\lambda_s(c, t)$ takes into account the following desired factors: the frequency of c in t, the number of *cphrs* related to c and the likelihood that the description of c in t would be referred for understanding *cphrs* in section s in the book.

Definition 3.2 *Given the stationary probabilities* $\pi(.,.)$ *associated with the random digression walks, define the significance score of a cphr* c *in section* t *for understanding section* s *as*

$$\lambda_s(c,t) := \sum_{v \in V:\bar{i}(v)=t, \bar{c}(v)=c} \quad \sum_{u \in V:\bar{i}(u)=s} \pi(u,v).$$

In the above definition, the inner summation is over all occurrences of *cphrs* in section s (corresponding to the digressions by readers who are unable to understand different *cphrs* in section s) and the outer summation is over all occurrences of *cphr* c in section t (corresponding to how often these readers refer to the description of c in section t).

3.5 Remarks

Number of concept references: We note that the number of desired references for a section can be determined in multiple ways. It can either be a small fixed number across all sections, or be determined based on the distribution of the significance scores for each section. In the latter case, given a limit k_{max} (say, 5) on the maximum number of references to be shown and a desired coverage κ (say, 75%), we can set k_s to be the minimum of (i) k_{max} and (ii) the number of top $\langle$*cphr*, section$\rangle$ pairs for section s needed to cover κ fraction of the sum of significance scores over all $\langle$*cphr*, section$\rangle$ pairs for this section.

Parameter Values: In our implementation of the reader model, there is effectively one parameter that determines the probabilities of the three types of transitions. When digression originates from a node, there are exactly two choices, to persist reading or to digress, and hence $\alpha + \beta = 1$. Similarly, for subsequent nodes in the digression, there are exactly two choices, to return back to starting node or to digress further, and hence $\gamma + \beta = 1$. Thus $\alpha = \gamma = 1 - \beta$. This relationship between α and γ is in agreement with the following natural intuition: one's tendency to read forward in a section is the same as the tendency to return to the starting point after a digression, since both these tendencies try to achieve the same goal of one's disciplined reading and completion of the entire book.

We experimented with different choices of the digression factor, and confirmed that the results from our reader model are robust to these choices. Higher digression factor would imply that the reader is more likely to digress to other sections when reading a section and hence would assign greater significance score to each $\langle$*cphr*, section$\rangle$ pair for understanding other sections. As sequential reading is the dominant mode in the reader model and hence large β values are undesirable, we considered the following values: $\beta = 0.1, 0.3$, and 0.5. First, we observed that the values of the significance scores of individual $\langle$*cphr*, section$\rangle$ pairs increase linearly with the digression factor. This follows from the random digression walk performed in the reader model. For example, when β increases by factor 3 from 0.1 to 0.3, so does the mass transferred from a *cphr* to a related *cphr* in the concept graph. Next, we measured the sensitivity of the digression factor on the relative significance of the $\langle$*cphr*, section$\rangle$ pairs since the study navigator makes use of only the relative ordering and not the absolute values. To do so, we computed the top 25 $\langle$*cphr*, section$\rangle$ pairs for each value of β and measured the numbers of inversions in the pairwise comparison of the orderings. Denote O_β to the top 25 $\langle$*cphr*, section$\rangle$ pairs for a particular β value and let $d(O_{\beta_1}, O_{\beta_2})$ denote the number of inversions between the two corresponding orderings. We found $d(O_{0.5}, O_{0.7}) = 11$; $d(O_{0.7}, O_{0.9}) = 10$;

and $d(O_{0.5}, O_{0.9}) = 18$. This shows that the number of inversions observed are small compared to the maximum inversions of $\binom{25}{2} = 300$. We got similar results when we measured the distance between each pair of orderings using Spearman's footrule. Since the relative ordering of ⟨*cphr*, section⟩ pairs remained quite robust, we use $\beta = 0.3$ in the experimental results reported in the paper. This choice corresponds to the reader starting a digression 30% of the time and persisting to read sequentially 70% of the time.

3.6 Relationship to Random Surfer Model and Personalized PageRank Computation

Our reader model might appear similar to the random web surfer model and personalized PageRank computation (Jeh and Widom, 2003). However, random walks used in these models have key differences. Represent the current state $\bar{V}$ of the random walk as a $|V|$-dimensional vector, where each field represents a ⟨section, *cphr*, position⟩ node in V and the fields are listed in the order of occurrences of *cphrs* in the book. Let $\bar{U}$ denote the preference vector corresponding to the return transition. Let A denote the transition probability matrix corresponding to the digression transition.

The preference vector is fixed in personalized PageRank computation. However, in our model, it gets updated during each persistence transition. Initially, $\bar{U} \leftarrow (1, 0, \ldots, 0)$. During each persistence transition, the preferred node (the field having unity value) gets shifted to the right. Formally, the preference vector gets updated as: $\bar{U} \leftarrow P\bar{U}$, where P is a permutation matrix (on $|V|$ dimensions) that transforms a unit vector along a given direction to the unit vector along the right adjacent direction, that is, $P_{i,i-1} = 1 \; \forall 2 \le i \le |V|$, $P_{1,|V|} = 1$ and all other entries of P are zero. As the preference vector changes over time, we need to keep track of both the preference vector (node from where the digression originated) and the current position of the reader (node in the digression) in order to compute the probability distribution of the reader's state after a certain number of transitions. However, we can obtain the following approximation by combining persistence and return transitions and assuming that the preference vector gets updated in each step:

$$\bar{V} \leftarrow \beta \cdot A\bar{V} + (1 - \beta) \cdot P\bar{U}.$$

Another difference is that digression occurs with a small probability and the return transition occurs with a large probability in our model (since persistent reading is the dominant behavior) whereas the return transition ("teleportation") occurs with a small probability in PageRank computations.

3.7 Study Navigator with Section References

The study navigator can be generalized to include only section references (that is, references at the granularity of a section) so that each section is treated as an atomic unit of reading. For this purpose, we compute the significance score $\tilde{\lambda}_s(t)$ of section t for understanding section s and then modify our algorithm to return an ordered list of top k section references for section s, based on the significance scores. $\tilde{\lambda}_s(t)$ can be computed either (1) by aggregating the significance scores at ⟨*cphr*, section⟩ granularity as: $\tilde{\lambda}_s(t) := \sum_{\textit{cphr}\ c \text{ in section } t} \lambda_s(c, t)$, or (2) modifying the reader model to treat each section as an atomic unit of reading. For example, the reader can be modeled to read an entire section before referring to other sections for *cphrs* that she could not understand. Similarly, whenever she digresses to a different section, she reads the digressed section from beginning to end, and then determines whether to digress to another section or return to the starting section.

Simplified Significance Score Computation: The significance score computation for section references can be approximated using the following simplified algorithm. For each *cphr* c in section s, determine other sections that mention c (say, using the back-of-the-book index if present) and then obtain the significance score of section t for section s as the number of distinct *cphrs* that are present in both s and t. This algorithm tries to simulate a reader who uses the back-of-the-book index to determine other sections to refer to while reading a section. This algorithm uses only information local to a section and other sections that share common *cphrs* while the reader model based algorithm performs a global computation using random walks. The former can be viewed as approximating the latter, analogous to how in-degree (a local measure) can be used to approximate PageRank (a global measure) (Fortunato et al., 2008).

4 User Study

We carried out extensive experiments to understand the performance characteristics of the study navigator system and present the results in this section. The goal of our evaluation is to determine whether users find the references provided by the study navigator system useful.

4.1 Methodology

4.1.1 Data Sets

We used a corpus of Indian high school textbooks published by the National Council of Educational Research and Training (NCERT). We selected this corpus because these books were readily available online. This corpus has also been used in prior studies related to textbooks (*e.g.*, (Agrawal et al., 2011)). The corpus consists of books from grades IX–XII, covering four broad subjects: Sciences, Social Sciences, Commerce, and Mathematics. For the purpose of in-depth analysis, we use Grade XII Economics textbook. We also present results for two other books from very different subjects: Grade X Science and Grade XII History. We observed similar results for other books in the corpus.

4.1.2 Concept Phrases and Relationship between them

If a textbook includes a back-of-the-book index (Mulvany, 2005), it can be used for obtaining concept phrases. Unfortunately, not all books contain such indices; *e.g.*, in a study reported in (Bakewell, 1993), only 55% of the 113 books examined included them. Moreover, tests of indexer consistency lend strong evidence to the subjective nature of human indexing. They reveal that indexers are likely to be in poor agreement among themselves, and the same indexer indexes the same document differently at different times (Fidel, 1994).

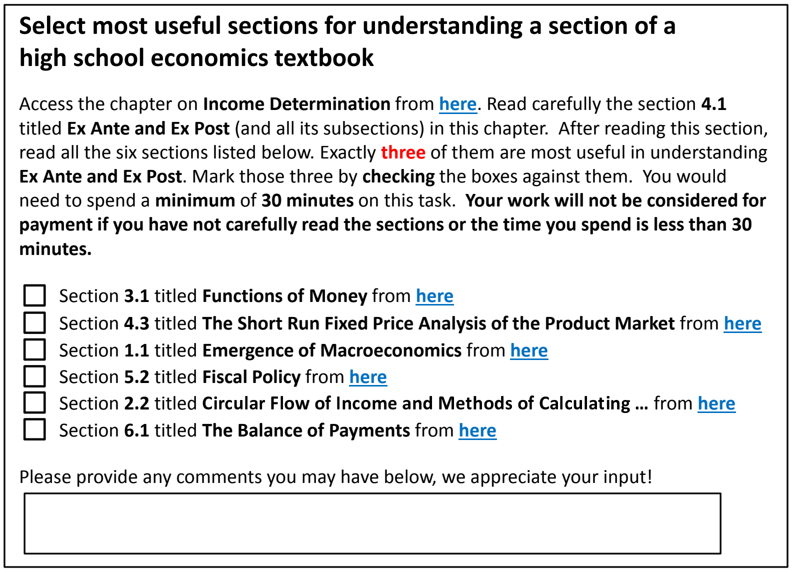
Multiple alternatives exist for algorithmically extracting concept phrases from a text ranging from detecting key phrases based on rules (grammar) to statistical and learning methods. In the former, the structural properties of phrases form the basis for the rule generation. In the latter, the importance of a phrase is computed based on statistical properties of the phrase (Jurafsky and Martin, 2008). After considerable experimentation with various approaches, we define *cphrs* to be terminological noun phrases (Justeson and Katz, 1995). We first form a candidate set of *cphrs* using linguistic patterns, with the help of a part-of-speech tagger (Toutanova et al., 2003). We use the pattern A^*N^+, where A refers to an adjective and N a noun, which was found to be particularly effective in identifying *cphrs* in (Agrawal et al., 2011). Examples of phrases satisfying this pattern include 'cumulative distribution function', 'fiscal policy', and 'electromagnetic radiation'. The initial set of phrases is further refined by exploiting complementary signals from different sources. First, WordNet (Fellbaum, 1998), a lexical database is used to correct errors made by the part-of-speech tagger. Next, both malformed phrases and very common phrases are eliminated, based on the probabilities of occurrences of these phrases on the Web, obtained using Microsoft Web N-gram Service (Wang et al., 2010). The reason for eliminating common phrases is that they would be already well understood.

We first attempted to induce relationships between concepts by mapping concept phrases to Wikipedia articles and use the link structure between the Wikipedia articles to infer relationship between concepts. We discovered the following issues. Many Wikipedia articles have asymmetric hyperlink structure, plausibly due to the encyclopedic nature of Wikipedia: there are relatively less links from articles on specialized topics to articles on more general topics. For instance, the Wikipedia article titled 'Gaussian surface' mentions 'electric field' 11 times but does not have a link to the latter. Furthermore, while Wikipedia provides good coverage for universal subjects like Physics and Mathematics, it has inadequate coverage for concepts related to locale-dependent subjects such as History. We, therefore, derive the relationship between *cphrs* directly from textbooks using co-occurrence. More precisely, we defined $R(c)$ to be the set of *cphrs* (including c) that co-occur with c in at least e sections such that both c and the co-occurring *cphr* c' occur within a window of size l in each of these e sections. The requirement of co-occurrence in multiple sections and co-occurrence within a window size ensures that we only consider *cphr* pairs that are significantly related to each other. We used $e = 2$ and $l = 500$ words, after confirming through sensitivity analysis that the results were not sensitive to these choices.

4.1.3 Helpfulness Index

Given the unavailability of a standard benchmark, we used the following procedure to evaluate the usefulness of the references proposed by the study navigator. For a given section, we first determined the top three sections referred by the study navigator. Ideally, we would have liked to compare them with those that an expert human judge (such as a teacher using the book or a student studying from the book) finds most useful after reading the entire book. In the absence of the availability of this subject population to us, we used the Turkers from the Amazon Mechanical Turk platform as judges. However, we could not recruit Turkers who were willing to read the entire book. We, therefore, changed the task to determine if the Turkers can differentiate the sections suggested by the study navigator from other sections. For this purpose, we obtained three arbitrary sections from the book and provided the original section along with these six sections to a judge, after scrambling the ordering between the referred sections. The judge was asked to read the original section, followed by all the six referred sections. Then the judge was asked to select exactly three most useful amongst the referred sections. This exercise was carried out using multiple judges.

We employed Borda's method to merge the votes of different judges. Borda's method strives to achieve a consensus ranking and satisfies desirable properties such as reversal symmetry (Saari, 2001). Each judge can be viewed as assigning one point each to three out of six



Select most useful sections for understanding a section of a high school economics textbook

Access the chapter on **Income Determination** from here. Read carefully the section **4.1** titled **Ex Ante and Ex Post** (and all its subsections) in this chapter. After reading this section, read all the six sections listed below. Exactly **three** of them are most useful in understanding **Ex Ante and Ex Post**. Mark those three by **checking** the boxes against them. You would need to spend a **minimum** of **30 minutes** on this task. **Your work will not be considered for payment if you have not carefully read the sections or the time you spend is less than 30 minutes.**

- ☐ Section **3.1** titled **Functions of Money** from here
- ☐ Section **4.3** titled **The Short Run Fixed Price Analysis of the Product Market** from here
- ☐ Section **1.1** titled **Emergence of Macroeconomics** from here
- ☐ Section **5.2** titled **Fiscal Policy** from here
- ☐ Section **2.2** titled **Circular Flow of Income and Methods of Calculating …** from here
- ☐ Section **6.1** titled **The Balance of Payments** from here

Please provide any comments you may have below, we appreciate your input!

Figure 3: A sample HIT

referenced sections and zero point each to the remaining three. Denote the total number of points a section obtained from the judges as its vote score. Consider the set of three sections with the largest vote score. These are the sections voted as most relevant by the judges according to Borda's method.

Out of these Borda winners, we determine the number of sections that were also suggested by the study navigator and define the *helpfulness index* as the number of study navigator references in this set divided by three (size of the set). Thus, in the absence of ties, the helpfulness index for each section will be equal to one of the following four values: 1, $2/3$, $1/3$, and 0. A value of 1 means that the top three sections voted by the judges were the same as the top three study navigator section references and a value of 0 means that the judges considered the arbitrary sections as more relevant than the study navigator section references.

However, it may not be possible to uniquely determine the set of three sections with the highest vote because of ties. In this case, we compute the helpfulness index by taking the expectation over all possible choices of this set, as explained in the following example. Let i_1, i_2 and i_3 be the study navigator section references with vote scores of 4, 3 and 3 respectively and r_1, r_2 and r_3 be the arbitrary section references with vote scores of 6, 3 and 2 respectively. The winner set always includes r_1 (section with the largest vote score) and i_1 (section with the second largest vote score). However, there are three possible candidates for the third section: i_2, i_3 or r_2. Thus, possible choices are $\langle r_1, i_1, i_2\rangle$, $\langle r_1, i_1, i_3\rangle$ and $\langle r_1, i_1, r_2\rangle$, with corresponding helpfulness index of $2/3$, $2/3$ and $1/3$ respectively. Hence, the helpfulness index in expectation will be $\frac{2/3+2/3+1/3}{3} = 5/9$. Thus, the helpfulness index for a section can be one of a small set of discrete values. In the results we present, in addition to the expected value, we also provide the two extreme possible values of the index, corresponding to the unfavorable choice (where we favor the inclusion of an arbitrary section in the winner set over a navigator section) and the favorable choice (where we favor a navigator section over an arbitrary section).

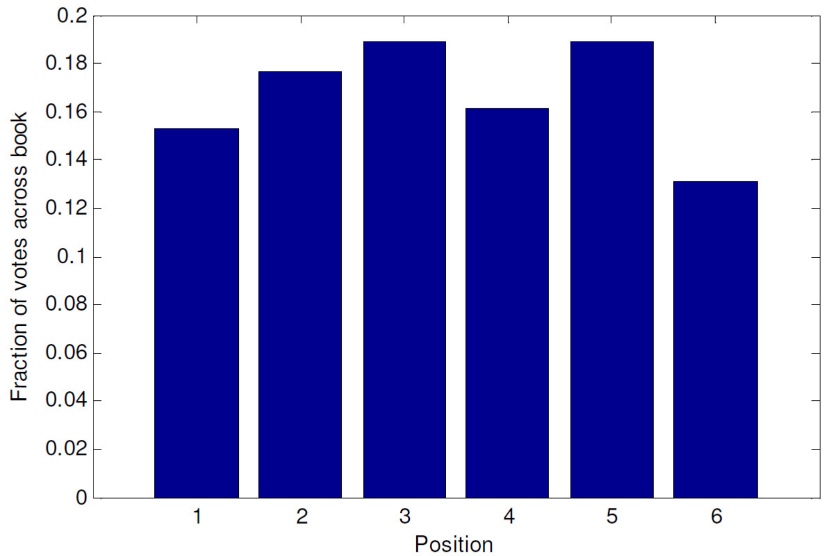


Figure 4: Distribution of all judgments across the six positions

4.1.4 Judges

Figure 3 shows the HIT (Human Intelligence Task) provided to the judges. In this example HIT, Sections 2.2, 4.3 and 5.2 are study navigator section references and Sections 1.1, 3.1 and 6.1 are arbitrary sections. Notice that the sections have been randomly ordered.

Each HIT was judged by seven judges. There were 158 distinct judges who took part in the study. We specified that a judge spend a minimum of half an hour on a HIT. We required our judges to have performed at least 1000 HITs in the past with an approval rating of at least 96%. Such judges have a strong interest in retaining their high rating. The judges had at least High School degree. We followed best practices suggested in the literature in accepting HITs (Amazon, 2011).

We also validated the quality of judgments along different dimensions. For example, Figure 4 shows the distribution of judgments across the six positions, that is, how often the judges marked the sections at position 1, 2, 3, 4, 5 and 6 respectively. We observe that the judgments did not exhibit position bias suggesting that the judges based their decisions after going through all six referred sections and were not unduly influenced by the (randomized) order in which the six sections were presented in each HIT. Similarly, we also verified that the judges did not have a backward bias (that is, tendency to favor earlier sections in the book) or a forward bias (that is, tendency to favor later sections). Figure 5 shows the distribution of judgments across the six positions for the top 20 judges who participated in the most number of HITs. This figure shows that the distribution of position-wise judgments varied across the judges, which indicates the absence of impostor judges who repeatedly judged a HIT using multiple identities.

4.2 Performance Results

The overall performance of the Study Navigator system for the three textbooks is shown in Figure 6. Each book is shown in the X-axis and the helpfulness index, averaged over all sections in the book, is shown in the Y-axis. The extreme values of the index are shown using an error

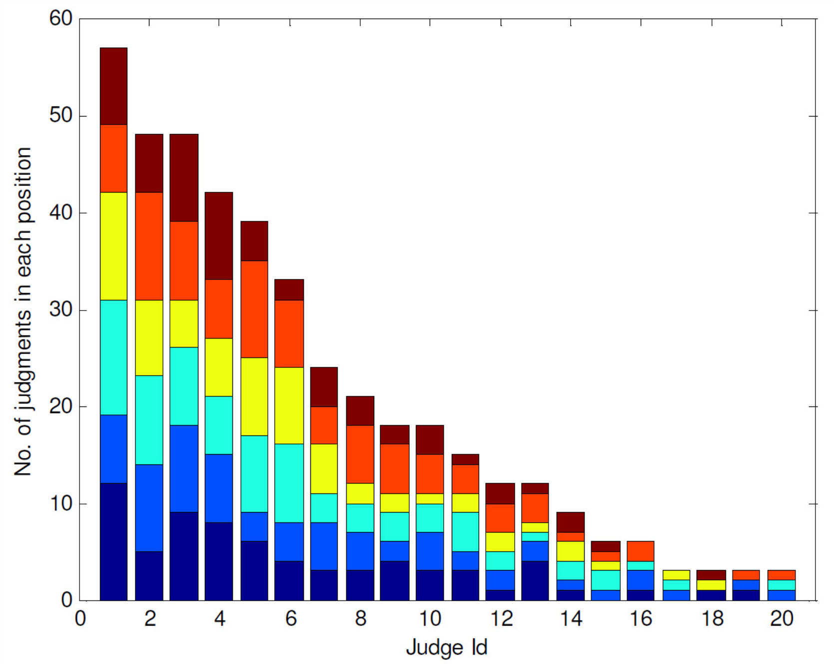


Figure 5: Distribution of position-wise judgments for top 20 judges who participated in the most number of HITs

bar. The results are very encouraging. The average helpfulness index for Grade XII Economics and Grade XII History books is 80% and 78% respectively, and this index is as high as 91% for Grade X Science book.

We next show the performance broken down at the section level. Figure 7 gives the fraction of sections with certain helpfulness index for the three books. For 71% of sections in Grade X Science book, the helpfulness index is 100%, that is, the judges considered all three study navigator section references as useful. For over 90% of sections, the helpfulness index exceeds 67%, that is, the judges considered at least two out of the three study navigator section references as useful. For 40% of sections in Grade XII Economics book and for 36% of sections in Grade XII History book, the helpfulness index is 100%. Furthermore, for 80% of sections in Grade XII Economics book and for 90% of sections in Grade XII History book, the judges considered at least two out of the three study navigator section references as helpful.

Grade X Science book has a higher helpfulness index because chapters are relatively self-contained in this book. On the other hand, in Grade XII Economics and Grade XII History books, even an arbitrary section can be considered relevant to the original section since common concepts are discussed across many chapters.

4.3 In-Depth Analysis

We next provide in-depth analysis of the results for Grade XII Economics book. We chose to present the analysis for this book because its helpfulness index is in between the indices for the other two books. We ourselves read the book carefully in order to be able to analyze the performance.

Figure 8 plots the helpfulness index for each section. For sections in which there were ties

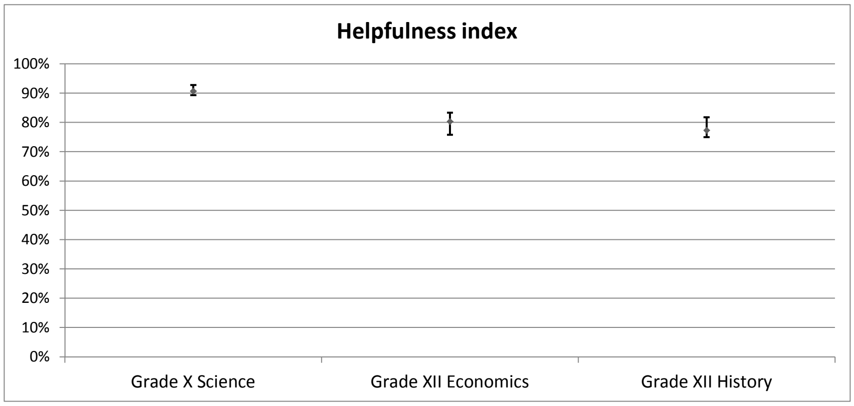


Figure 6: Performance of Study Navigator system for the three textbooks

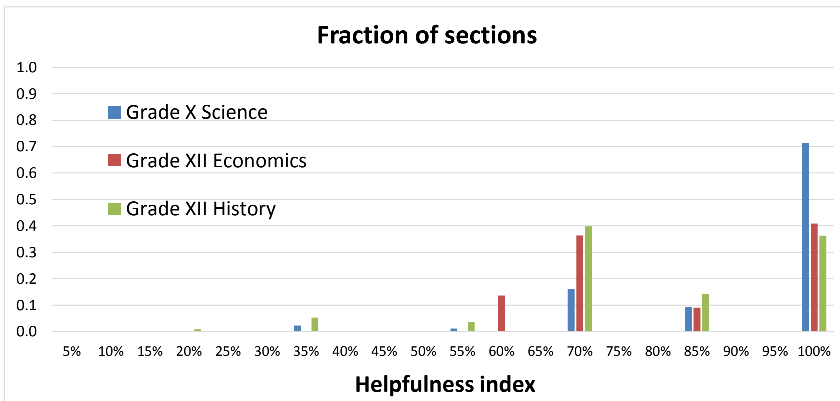


Figure 7: Fraction of sections with different helpfulness index in the three textbooks

in the judgments, we also show the extreme values using an error bar in addition to the expected value. We observed that for 9 out of 22 sections, the judges unanimously preferred all three of the study navigator sections over the arbitrary sections. For another 10, judges preferred at least two of the study navigator sections. Only for three sections, judges selected one study navigator section, assuming ties were broken in favor of arbitrary sections. There was no such section when the ties were broken the other way.

For further analysis, we employ the schematic shown in Figure 9.

Section 4.1: We first discuss one of the sections for which the top three sections voted by the judges are identical to the three study navigator sections. Figure 9(a) shows the schematic for Section 4.1 titled "Ex ante and ex post" which is part of the chapter on income determination. This section explains the differences between the planned (ex ante) and actual (ex post) values of consumption, investment and aggregate demand of final goods in an economy, and the determinants of the ex ante values of these variables. The top three study navigator section references for this section are Section 2.2 ("Circular flow of income and methods of calculating national income"), Section 4.3 ("The short run fixed price analysis of the product market") and

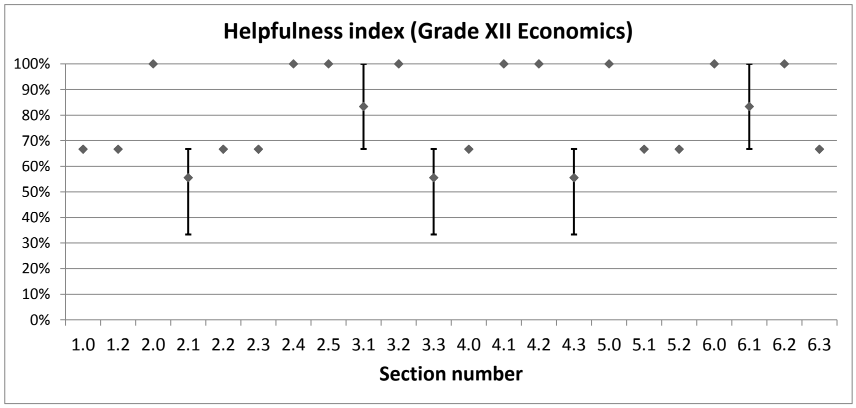
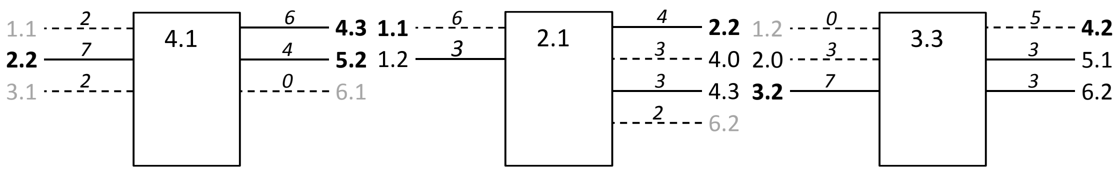


Figure 8: Helpfulness index for sections in Grade XII Economics textbook



(a) Section 4.1 (b) Section 2.1 (c) Section 3.3

Figure 9: References provided to judges and their votes (Grade XII Economics textbook). In this schematic, the rectangle represents the original section. The thick lines point to the three study navigator section references and the dashed lines point to the arbitrary sections. Sections occurring before the original section in the book are placed to the left and those occurring after the original section are placed to the right. The number of judges who voted for a section is shown above the corresponding line. The clear winners are indicated in bold face, clear losers in light face, and ties in normal face.

Section 5.2 ("Fiscal policy"). Section 2.2 presents the circular flow of income and explains three different methods for computing national income, and thus is useful for understanding the relationship between consumption, investment and aggregate demand in the context of the current section. Similarly, Section 4.3 discusses the relationship between demand, supply and price of final goods, and hence helps the reader better understand why ex post values can differ from ex ante values. Likewise the discussion of fiscal policy in Section 5.2 helps the reader appreciate how government policies can result in ex post values differing from ex ante values. Thus, the helpfulness index for this section is 100%. Note that the judges preferred by wide margin Section 4.3 over arbitrary Sections 1.1 and 3.1 that come earlier as well as Section 6.1 that comes later. It suggests that the judges diligently went through the original section as well as the six candidate sections and did not blindly favor back or forward references.

We next report our analysis of two of the three sections that had the least helpfulness index. The conclusions from the third section (Section 4.3) were similar.

Section 2.1: Figure 9(b) shows the schematic for Section 2.1 which is part of the chapter on national income accounting. This section introduces basic concepts in macroeconomics such as production & consumption, final goods & intermediate goods, consumption goods & capital goods, stocks & flows and investment. The three study navigator section references for this section are Section 2.2 ("Circular flow of income and methods of calculating national income"), Section 4.3 ("The short run fixed price analysis of the product market") and Section 1.2 ("Context of the present book of macroeconomics"). Section 2.2 presents the circular flow of income and explains three different methods for computing national income, and in the process, describes the relationship between different concepts introduced in the current section. Hence it can lead to a deeper understanding of Section 2.1. The dissonance that merits discussion is why judges preferred 1.1 over 4.3. We found that Section 1.1 is a short section discussing the emergence of the subject of macroeconomics and provides a historical perspective to the basic concepts of the subject. Section 4.3 on the other hand discusses the relationship between equilibrium output, aggregate demand, supply and price of final goods. Thus, Section 1.1 will be preferred by a reader who wants to be reminded of the context in which she is reading the current section, whereas Section 4.3 might appeal to a reader who wants to learn more about the relationship between concepts introduced in the current section. In general, our algorithm tends to rank sections that have deeper explanations higher.

Section 3.3: Figure 9(c) shows the schematic for Section 3.3 which is part of the chapter on money and banking. This section describes the role of the central bank in regulating the supply of money through its instruments of monetary policy. It is primarily focused on the money creation in the banking system with emphasis on the internal operations of maintaining reserve and loaning out money for wealth creation. Towards this end, the section describes how the instruments of money creation are used in stabilizing the stock of money in the economy from external shocks. The concept of external shocks is illustrated using an example of investors around the world buying in domestic markets using foreign currency and how this activity can lead to inflation, if not kept in check through the process of sterilization by the central bank. The three study navigator section references for this section are Section 6.2 ("Foreign exchange market"), Section 3.2 ("Demand for money") and Section 5.1 ("Components of the government budget"). Section 3.2 discusses the motives for holding money which is needed for understanding the current section, and is unanimously liked by the judges. We investigate why judges marginally preferred Section 4.2 (an arbitrary section) over Section 6.2 (a study navigator section). It turns out that Section 4.2 describes graphical techniques for analyzing relationships between mathematical variables. Section 6.2 on the other hand explains how foreign exchange rates are determined and studies how differences in inflation and interest rates between countries can lead to adjustment in exchange rates. Thus, Section 4.2 is likely to be preferred by a reader who is looking for tools to plot and visualize the equations in the current section, whereas Section 6.2 might appeal to a reader who wants to understand the illustration used for explaining external shocks. Explanation for Section 5.1 is similar.

Summary: This in-depth analysis reveals that the judges found the references provided by the study navigator to be helpful. In the cases where the judges preferred references other than those provided by the study navigator, it was mostly for sections that reminded them of the material covered earlier, or described applications of the material being discussed, or provided general tools (*e.g.*, how to interpret a graph).

5 Student-Specific Navigator

We now describe the extension of study navigator to incorporate the information processing preference of the student. In the student-specific navigator, we associate with each student the extent to which the student is disposed to referring later sections and denote it as the *curiosity factor*. Let $\gamma \in [0, 1]$ represent the curiosity factor. A student preferring to refer only the prior sections has a curiosity factor of 0 while a student wanting to refer only the later sections has a curiosity factor of 1. Thus we allow students to control the balance between sections that help refresh material already read vs. sections that provide more advanced information.

We modify the reader model (§3.1) to take into account the curiosity factor, and compute the significance scores based on this new model as in §3.4. Whenever the reader seeks explanation of a *cphr* c in section i, she first picks a related *cphr* c' from $R(c)$ with equal probability. Then, she tosses a biased coin for which the probability of head equals γ. If the outcome is a tail (head), the reader chooses an occurrence of c' occurring before (after) section i, and refers to the corresponding section i' to learn more about c'. Thus, the modification to the model is that instead of choosing an occurrence of a *cphr* c' amongst all occurrences of c' in the book with equal probability at each step, the reader favors a prior or a later occurrence depending on her curiosity factor. The subsequent digressions of the reader proceed in a similar fashion as before, but are biased by her curiosity factor.

5.1 User Study

The goal of this study was to first validate the existence of users with different reading styles, and then to evaluate whether the corresponding study navigator is useful for them. For this study, we used 0.25 and 0.75 as two representative values of the curiosity factor. The choice, $\gamma = 0.25$ (0.75) represents diligent (curious) readers and we denote the corresponding study navigator as diligent (curious) navigator.

5.1.1 Existence of Diligent and Curious Users

Ideally we would have liked to make use of the manner in which students read from textbooks to determine their reading style. Since the adoption of electronic textbooks is still in infancy and we did not have access to usage logs, we resorted to the following procedure. For a given section, we determine the top three sections each referred by the diligent and curious navigators. We now ask a user (a Turker on the Amazon Mechanical Turk) to read the original section, followed by all the six referred sections (after randomly ordering the referred sections). The user then selects exactly three most useful sections for understanding the section out of the six referred sections. The results for each section were examined by fifteen users. We carried out this procedure for half of the sections in Grade XII Economics book (and used the remaining sections for evaluating the usefulness of the study navigator in §5.1.2).

We analyzed the extent to which each user preferred references from the diligent vs. the curious navigator. For this purpose, we computed the number of votes for references from diligent and curious navigators respectively for every user. We only included users who participated in at least four sections, corresponding to a total of 12 votes. We define the *curiosity index* as the difference between the votes for curious vs. diligent navigator divided by the total number of votes. This index can range from -1 to 1, with -1 corresponding to a user strictly preferring diligent references, 1 to a user strictly preferring curious references, and 0 to a user equally preferring

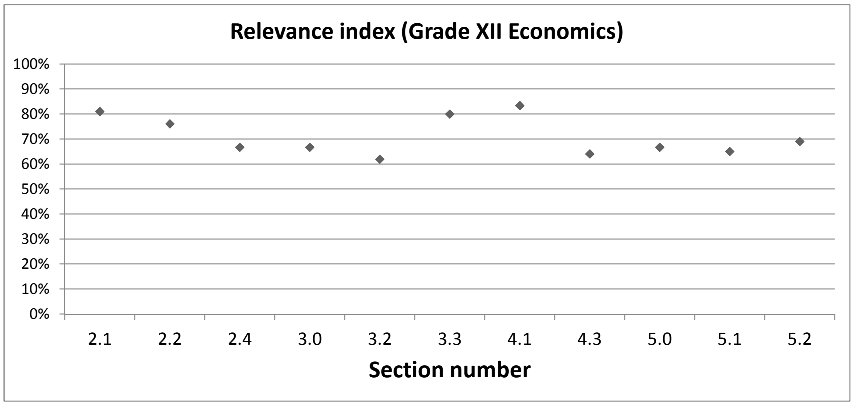


Figure 10: Relevance index for sections in Grade XII Economics textbook

both types of references. We define the set of diligent (curious) users to be those with curiosity index $<$ -0.25 ($>$ 0.25). Using this procedure, we obtained 12 diligent and 5 curious users.

5.1.2 Usefulness of the Student-Specific Navigator

Given the sets of diligent and curious users, we evaluated whether the corresponding study navigator references are useful for these readers. We performed this experiment for half the sections in Grade XII Economics book that were not used in determining user types (see §5.1.1). For a given section, we determined the top three sections referred by the diligent navigator as well as the top three sections referred by the curious navigator. We now provide the original section along with the top three sections referred by the diligent (curious) navigator to a diligent (curious) user, after randomly ordering the referred sections. The user was asked to read the original section, followed by all the three referred sections. Then the user was asked to mark whether each referred section was useful for understanding the original section. We then computed the *relevance index* as the average fraction of references that the users considered useful.

The relevance index, averaged over all sections in Grade XII Economics book used in the evaluation, is 71%. Figure 10 shows the relevance index for different sections in this book (recall that half the sections were used for determining diligent and curious users). We observe that for 8 out of 11 sections, users considered at least two of the study navigator sections on average as useful. Thus, we conclude that the references provided by the student-specific navigator were found useful by respective type of users. We also carried out in-depth analysis similar to §4.3 that corroborated this result.

6 Concluding Remarks

The future of textbooks is electronic. Sven Birkerts thus opined about this brave new world (Birkerts, 2006): "What the writer writes, how he writes and gets edited, printed and sold, and then read – all the old assumptions are under siege." However, the current technology is still quite nascent (Thayer et al., 2011). We anticipate a surge of innovations to make studying from electronic textbooks much more pleasant and productive. Electronic textbooks as a medium is fundamentally different from printed textbooks, and hence has the potential to enable new kinds of functionalities.

We presented *study navigator*, one such novel functionality that can enhance the experience of studying from electronic textbooks. The goal of the study navigator is to help a student learn the material better and faster by providing easy access to concepts explained elsewhere in the book that are most relevant for understanding the present section. Our major contributions include:

- A complete design and implementation of the study navigator system.
- A novel reader model for textbooks and an algorithm for generating the study navigator based on this model.
- An extension of the study navigator and the reader model to accommodate the information processing preference of the student. Specifically, this specialization allows a student to control the balance between references to sections that help refresh material already studied vs. sections that provide more advanced information.
- An end-to-end evaluation over a corpus of high school textbooks, demonstrating the effectiveness of the proposed system across textbooks on different subjects from different grades.

Though currently unavailable, rich data on reader's actions can be obtained once electronic textbooks are widely deployed. In the future, we would like to investigate how reader's actions can be incorporated to further enhance the study navigator. For example, collaborative filtering techniques can be used to recommend sections based on the aggregate behavior of a large number of readers. The design of study navigator could be generalized to apply to a collection of textbooks (instead of individual textbooks). For example, the study navigator can be extended to provide easy access to concepts explained in textbooks from earlier grades as well, by treating a sequence of textbooks on the same subject across consecutive grades as a single meta-textbook. Similarly, the study navigator can allow linkages across textbooks on related subjects since such textbooks are likely to contain a large number of common *cphrs* as well as related *cphrs*. There are inherent limitations to performing user studies using Mechanical Turk platform. Designing sound evaluation methodology and performing user study involving teachers and students using the books is fodder for promising future research. A related direction for future work is to investigate the comparison of study navigator results with alternative methods such as (a) closest sections obtained using distance measures from the literature on text mining, clustering, and nearest neighbor computation, (b) sections in close proximity to the current section, and (c) sections that share most concept phrases with the current section. Another related direction is to empirically analyze the effect of the quality of inputs (concept phrases and the relationship between them) on the study navigator results, and in particular, to measure the stability of the results to minor perturbations to the inputs. We would also like to explore specializations of the study navigator for additional learning styles beyond the information processing orientations of the reader. More generally, we are interested in designing tools that make use of the electronic format to imbue unique functionality in electronic textbooks along the lines described in the introduction to this paper.

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