

Problems



Institution





Student

Institutional Problems



No insight into how institution is doing



Difficult to track and identify what to focus on



Manual remediation workflow



Lawsuits because of legal requirements

Instructor Problems



Lack of awareness of what to do



Lack of understanding on how it can affect students



Lack of guidance on how to improve accessibility

Student Problems



Explicit alternative format requests



Long delays on receiving requested format



Excludes many students



Closely related to quality and usability



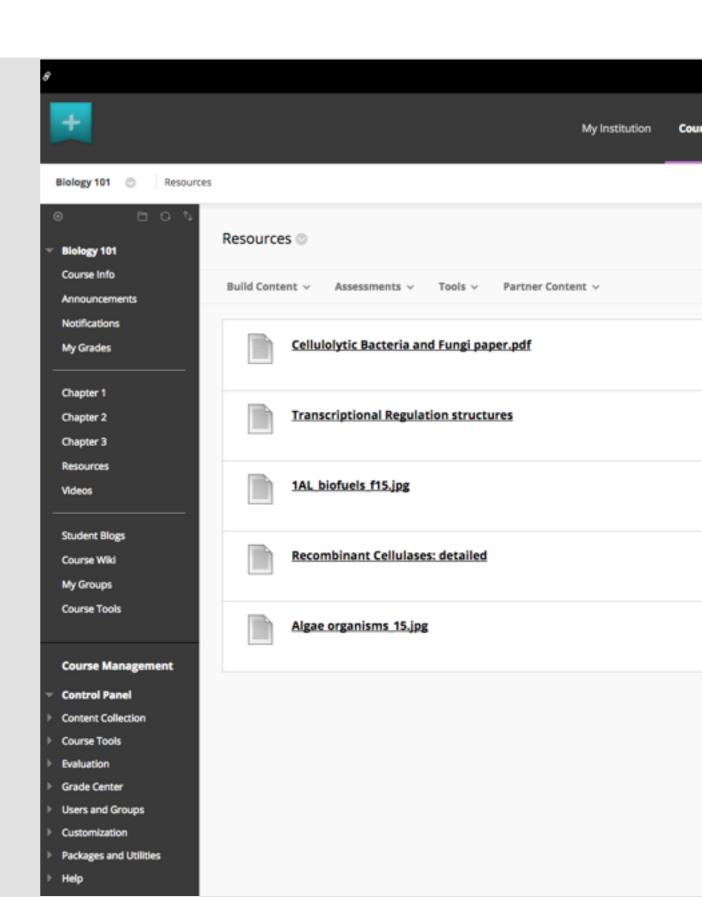
Learning Management System

- The Learning Management
 System is an important player in this
- Committed to providing Ally to everyone, including non-Blackboard products
- Potential for other integrations



Workflow

 Instructor adds course content to course site



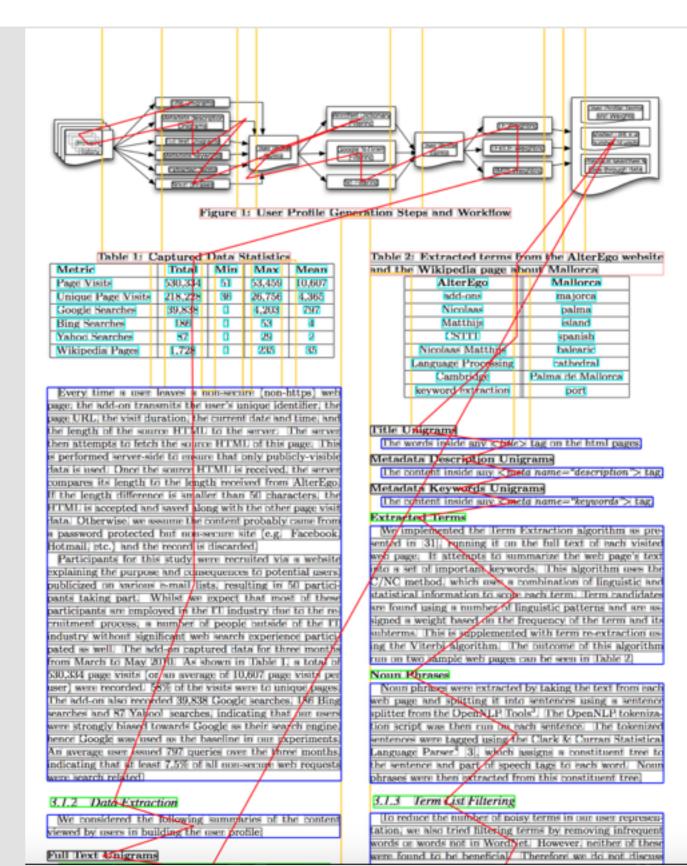
Automated Accessibility Checklist



- Automated accessibility checklist based on content type
- Based on WCAG 2.0 AA

Machine Learning Algorithms

- Full structural and visual analysis to learn semantics of document
- Identify headings, heading structure, paragraphs, footers, tables, lists, mathematical formulas, etc.



Alternative Accessible Versions



3.1.4 Term Weighting

After the list of terms has been obtained, we compute weights for each term in three ways.

TF Weighting

The most straightforward implementation we consider in form Frequency (TF) weighting. We define a frequency wetor \tilde{F} that contains the frequency counts of a given term t_i for all of the input data sources, as shown in Equation (1). For example, $f_{\rm MC}$ is the number of times a given term t_i occurs in all of the titles in the user's browsing history. We calculate a term weight based on the dot product of these frequencies with a weight vector d:

$$\vec{F}_{i_1} = \begin{bmatrix} f_{100n_{i_1}} \\ f_{200n_{i_2}} \\ f_{100n_{i_1}} \\ f_{100n_{i_1}} \\ f_{100n_{i_1}} \end{bmatrix}$$
(1)

$$w_{TF}(t_i) = \vec{F}_{t_i} \cdot \vec{a}$$
 (2)

For simplicity, we limit curselves to three possible values for each weight α_i : 0, ignoring the particular field, 1, including the particular field, and $\frac{1}{N_c}$, where N_c is the total number of terms in field 4. This gives more weight to terms in shorter fields (such as the meta keywords or title fields). We call the last relation weighting.

TF-IDF Weighting

The second option we consider in TF IDF (or Tren Frequency, leverse Document Frequency) weighting. Here, words appearing in many documents are down weighted by the inserse document frequency of the terms:

$$\mathbf{w}_{TFILF}(t_i) = \frac{1}{log(DF_{\tau_i})} \times \mathbf{w}_{TF}(t_i)$$
 (3)

To obtain IDF estimates for each term, we use the inverse document frequency of the term on all web pages using the Google N-Gram corpus².

Personalized BM25 Weighting

The final weight method we consider was proposed by Torons et al. [28], which is a modification to BM25 term weighting:

3.2 Re-ranking Strategies

Like previous work, we use the user profile to re-rank the top results returned by a search engine to bring up results that are more relevant to the user. This allows us to take advantage of the data search engines use to obtain their intial ranking, by stacting with a small set of results that can then be personalized. In particular, [28] noted that chances are high that even for an ambiguous query the search engine will be quite successful in returning pages for the different meanings of the query. We opt to retrieve and re-rank the first 50 results retrieved for each query.

3.2.1 Scoring Methods

When remarking, each candidate document can either be scored, or just the snippets shown on the search engine result page can be scored. We focus on assigning scores to the search snippets as it was found to be more effective for re-ranking search results by Toevan et al. [36]. Also, using search snippets allows a straightforward client-side implementation of search personalization. We implemented the following four different scoring methods:

Matching

For each word in the search snippet's thie and summary that is also in the user's profile, the weight associated with that term will be added to the snippet's score:

$$score_H(s_i) = \sum_{i=1}^{N_{r_i}} f_{t_i} \times w(t_r)$$
 (5)

where $N_{\rm e}$, represents the total number of unique words within the snipper's title and summary, and $f_{\rm e}$, represents the number of occurrences of $t_{\rm e}$ within the snippet. Words in the snippet title or summary but not in the user's profile do not contribute towards the final score. This method is equivalent to-taking the dot product between the user profile vector and the snippet vector.

Unique Matching

A second search enippet scoring option we consider involves counting each unique word just once:

$$core_{UM}(s_i) = \sum_{i=1}^{N_{s_i}} w(t_i)$$
 (6)

Language Model

CHAPTER I

Down the Rabbit-Hole

Alice was beginning to get very tired of sitting by her sister on the bank, and of having nothing to do: once or twice she had peeped into the book her sister was reading, but it had no pictures or conversations in it, and what is the use of a book,' thought Alicewithout pictures or conversation?'

So she was considering in her own mind (as well as she could, for the hot day made her feel very sleepy and stupid), whether the pleasure of making a daisy-chain would be worth the trouble of getting up and picking the daisies, when suddenly a White Rabbit with pink eye

There was nothing s that: nor did Alice th

much out of the way to itself, Oh dear! Oh

(when she thought occurred to her that wondered at this, it seemed quite natural bit actually TOOK A WAISTCOAT-POCK and then hurried or feet, for it flashed achad never before see waistcoat-pocket, or it, and burning with across the field after just in time to see it

HTML

High quality semantic HTML version of the content

Enhance original

Automatically inject fixes into the original document

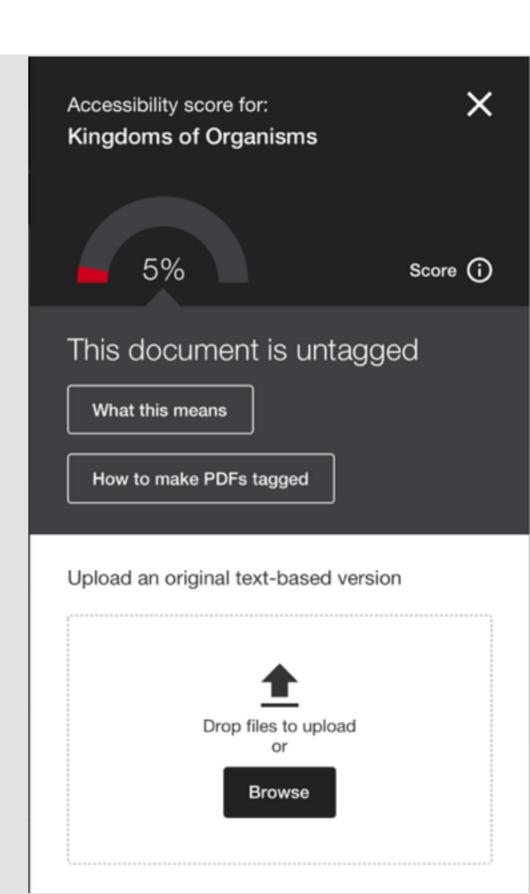
Other alternative formats

ePub, audio, electronic braille, etc.

Instructor Feedback

 Provide feedback to instructors about accessibility of their course content

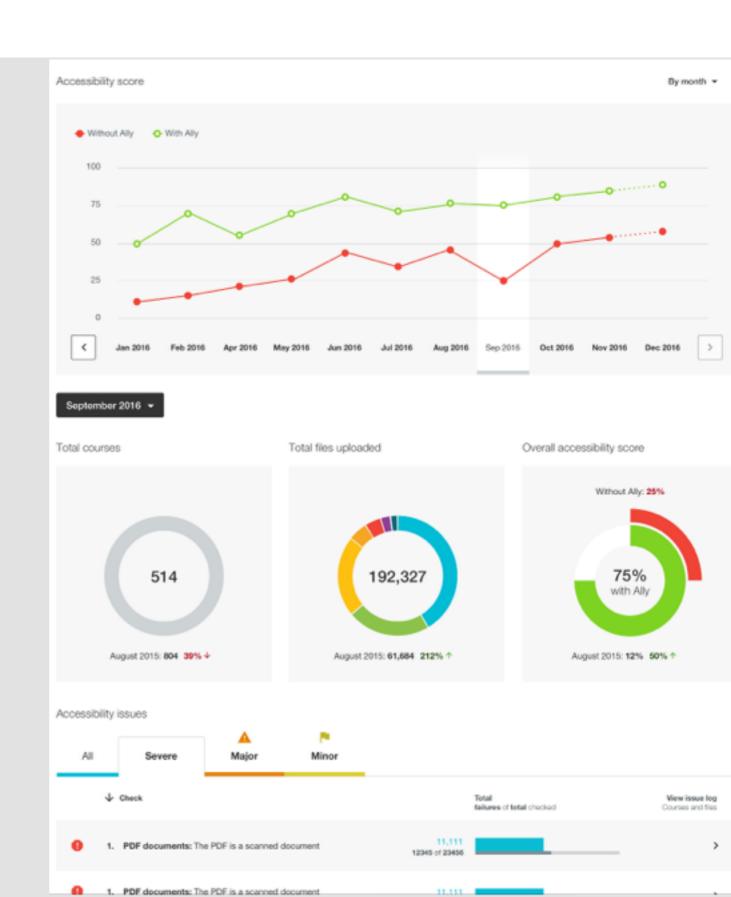
- Provide guidance on how to fix accessibility issues
- Aims to generate change in behavior over time



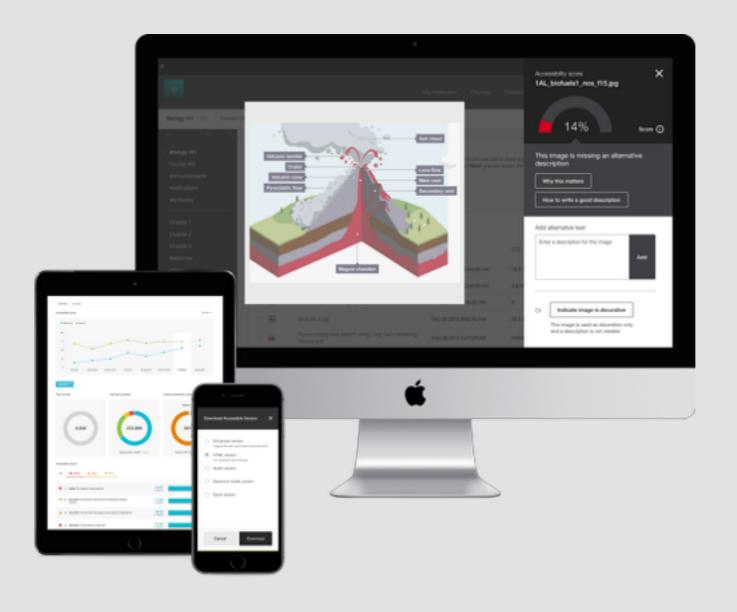
Institutional Report

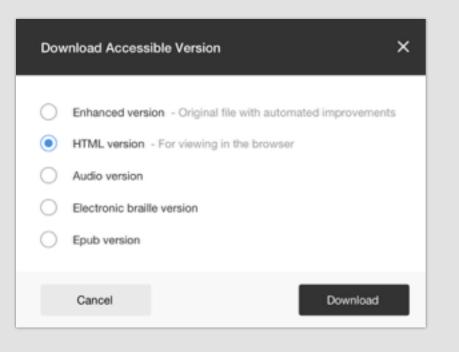
 Provide detailed understanding of how institution is doing

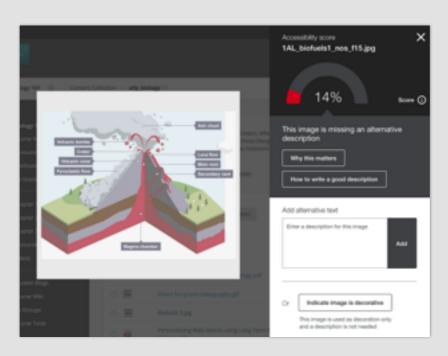
 Helps identify where problem areas are, what to focus on, who to target, etc.



Demo









Alternative Accessible Versions

Automatically checks for accessibility issues and generates alternative accessible formats

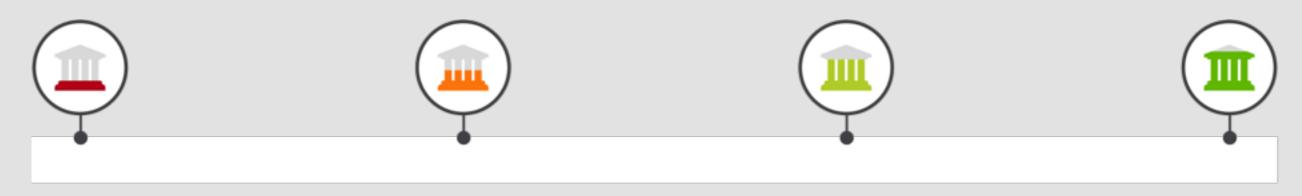
Instructor feedback

Guides instructors on how to improve the accessibility of their course content and alters future behavior

Institutional report

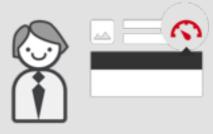
Provides detailed data and insights to help further improve course content accessibility at the institution

Accessibility Spectrum





Automated Accessible versions



Instructor feedback

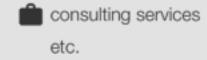


Institutional report

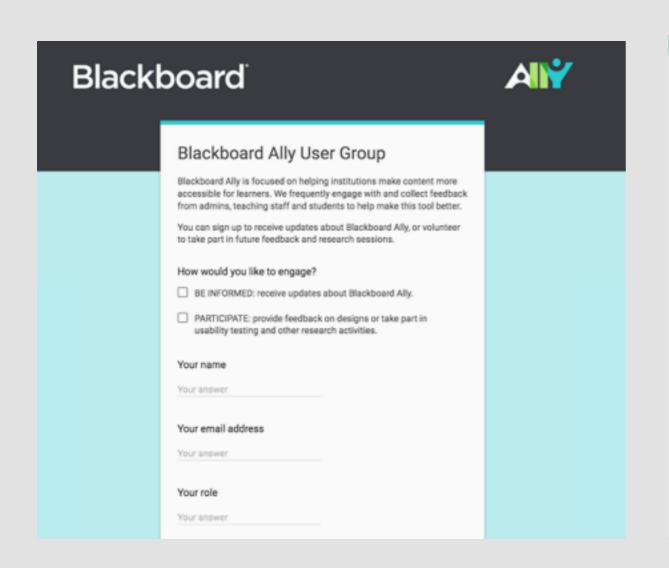
INFORMS:







Ally User Group



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- Participate in UX research, usability testing, early access, etc.

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