A Transfer Learning Pipeline for Educational Resource Discovery
with Application in Leading Paragraph Generation

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Abstract

Effective human learning depends on a wide selection of educational materials that align with the learner’s current understanding of the topic. While the Internet has revolutionized human learning or education, a substantial resource accessibility barrier still exists. Namely, the excess of online information can make it challenging to navigate and discover high-quality learning materials. In this paper, we propose the educational resource discovery (ERD) pipeline that automates web resource discovery for novel domains. The pipeline consists of three main steps: data collection, feature extraction, and resource classification. We start with a known source domain and conduct resource discovery on two unseen target domains via transfer learning. We first collect frequent queries from a set of seed documents and search on the web to obtain candidate resources, such as lecture slides and introductory blog posts. Then we introduce a novel pretrained information retrieval deep neural network model, query-document masked language modeling (QD-MLM), to extract deep features of these candidate resources. We apply a tree-based classifier to decide whether the candidate is a positive learning resource. The pipeline achieves F1 scores of 0.94 and 0.82 when evaluated on two similar but novel target domains. Finally, we demonstrate how this pipeline can benefit an application: leading paragraph generation for surveys. This is the first study that considers various web resources for survey generation, to the best of our knowledge. We also release a corpus of 39,728 manually labeled web resources and 659 queries from NLP, Computer Vision (CV), and Statistics (STATS).

Keywords: web resources, transfer learning, text classification, natural language generation

1. Introduction

People rely on the internet for various educational activities, such as watching lectures, reading textbooks, articles, and encyclopedia pages. One may wish to develop their knowledge in a familiar subject area or to learn something entirely new. Many online tools enable and promote independent learning (Montalvo et al., 2018; Romero and Ventura, 2017; Fabbri et al., 2018; Li et al., 2019a). A subset of these platforms provide primary literature resources (e.g. publications), such as Google Scholar\footnote{https://scholar.google.com/} and Semantic Scholar\footnote{https://www.semanticscholar.org/} As an alternative to these advanced materials, other educational platforms such as MOOC.org\footnote{https://www.mooc.org/} deliver free online courses. Also, unstructured searching on the internet is a popular method to discover other useful resources, such as blog posts, GitHub projects, tutorials, lecture slides and textbooks. Rather than diving into the technical details, these secondary literature resources provide a broad overview of the given domain, which is more valuable for beginners. Still, sifting through this material can be challenging and time-consuming, even if the learner is simply looking for a general and reliable introduction into a new subject area.

Publicly accessible data repositories that focus on gath-
2. Educational Resource Discovery Pipeline

We propose the Educational Resource Discovery (ERD) pipeline that aims at automatically recognizing high-quality educational resources. We model this problem as a resource classification task. Given a resource $r$, where $r$ can be any source type such as web page, PDF file and PPTX file, and we can obtain a list of features by feature engineering; based on these features, $r$ is classified as positive if it is a high-quality resource, otherwise negative. We introduce the definition of high-quality resource in detail later. We illustrate the ERD pipeline in Figure 1. It consists of data collection, feature extraction and resource classification.

2.1. Data Collection

2.1.1. Queries for search

In this step, we need to conduct a list of meaningful and fine-grain search queries to start. These search queries will then be applied to online search engines for web resources. Queries can be borrowed from external corpora or extracted from existing seed documents (e.g., textbooks). We focus on three domains: NLP (natural language processing), CV (computer vision) and STATS (statistics). We utilize external topic lists provided by LectureBankCD (Li et al., 2021), in which there are 322 NLP-based and 201 CV-based topics from crowdsourcing. For STATS, we extract a list of fine-grained terms from several seed documents, including several textbooks. These terms contain frequent keywords and phrases that are extracted by TexRank (Mihalcea and Tarau, 2004), a statistical method to keyword ranking. In total, we end up with 322, 201 and 137 queries for NLP, CV and STATS domains.

To craft our search engine queries, we leverage advanced search conditions: filetype and site (website). Specifically, we consider three file types: PDF, PPTX/PPT, and HTML. Moreover, according to the TutorialBank corpus (Fabbri et al., 2018), resources clustered by the components of their URL possess highly correlated educational content. Thus, we prioritize restricting our queries to websites that consistently provide high-quality resources. We select the top sites from the manually-created TutorialBank corpus and incorporate them into our search queries, as exemplified in Table 1. We also include the “.edu” top-level domain as a special case for our search queries in order to capture general educational resources. Finally, we combine our query terms with the website and filetype constraints: e.g., “word embeddings filetype:pdf”. We also augment the original query by generating a disjunction of its variations: e.g., “stochastic gradient descent” becomes “stochastic gradient descent OR SGD”. Table 1 displays several sample queries.

Once the queries are generated, we leverage three well-established online search engines: DuckDuckGo (https://duckduckgo.com/), Yahoo (https://search.yahoo.com/) and Bing (https://www.bing.com/) to obtain our candidate resources. The top $N$ URLs (where $N$ is determined from the domain, file type and site type, varying from 20 to 100 to control the total number of resources we want to collect) for a given query are cached after checking their HTTP response status and ensuring that a URL has not already been collected as part of another query. Moving forward, the documents pointed to by all of

| Positive Resources | Application |
|--------------------|-------------|
| towardsdatascience.com | datahacker.rs |
| medium.com | hackernoon.com |
| www.analyticsvidhya.com | skymind.ai |
| www.kdnuggets.com | maelfabien.github.io |
| machinelearningmastery.com | rubikscode.net |
| paperswithcode.com | research.googleblog.com |

Table 1: Top sites found in the TutorialBank corpus.
these URLs were automatically downloaded and parsed for their features. Certain features, such as the number of authors, were collected using heuristics that accounted for most of the variability within the diverse dataset. The ERD Pipeline’s parsers use the pdfminer, grobid libraries for PDF files, Apache Tika for PPTX/PPT and BeautifulSoup for HTML.

2.1.2. Annotation
After collecting all resources, the next step is to assign a binary label to each resource based on its quality. Our annotators consist of 7 graduate and senior college students with a solid background in NLP, CV, and STATS. A resource is annotated as positive if it is a high-quality one. Guidelines for a positive (high-quality) resource are:

- **Informative and relevant**: introducing basic knowledge about a specific topic. For example, tutorials, introductions, explanations, guides.
- **Papers and lecture slides**: papers and lecture notes about a topic in the correct domain.
- **Other secondary literature articles**: i.e., blog posts with informative descriptions, definitions, and code blocks.

The annotation criteria for a negative (poor-quality) resource are:

- **Not informative**: dataset/software/tool download page without introductory descriptions, such as a paper abstract page (not the paper content), a download page with links.
- **Irrelevant**: not showing correct content, broken URLs, URLs with not enough or no text (video or image only).
- **No knowledge included**: such as a course landing page, a person’s personal website page.
- **A list of resources/datasets**: containing only links to other pages.

Finally, to measure the inter-coder agreement of the labels, we randomly picked 100 resources and asked each annotator to provide labels independently. Krippendorff’s alpha (Krippendorff, 2011) on this sample evaluated to 0.8344, indicating a high degree of consistency amongst all annotators.

We detail statistics about our collected dataset in Table 2, providing the total counts by filetype and domain. From the three domains, we collected 39,728 valid resources using 659 distinct queries and achieved a total positive rate of 69.05%.

In Table 3, we show token-level and sentence-level statistics on the extracted free text of the collected data.

![GitHub](https://github.com/pdfminer/)
![Kermitt](https://github.com/kermitt2/grobid)
![Tika](https://tika.apache.org/)
![Crummy](https://crummy.com/software/BeautifulSoup/)

### NLP Sample Queries
- “markov decision processes” site:edu filetype:.pdf
- “sentiment analysis” site:edu filetype:.pdf
- “unlexicalized parsing” site:kdnuggets.com filetype:.html
- “semantic parsing” site:edu filetype:.pdf
- “information retrieval” site:edu filetype:.pptx
- “monte carlo methods” site:rubikscode.net filetype:.html
- “natural language processing intro” site:edu filetype:.pdf
- “sequence to sequence” site:edu filetype:.pptx
- “naive bayes” site:paperswithcode.com filetype:.html
- “latent dirichlet allocation” site:edu filetype:.pptx

### CV Sample Queries
- “epipolar geometry” site:edu filetype:.pptx
- “particle filters” site:hackernoon.com filetype:.html
- “image registration” site:edu filetype:.pdf
- “reflectance model” site:edu filetype:.pptx
- “shading analysis” site:skymind.ai filetype:.html
- “imaging geometry and physics” site:edu filetype:.pdf
- “texture classification” site:edu filetype:.pptx
- “gibbs sampling” site:kdnuggets.com filetype:.html
- “image thresholding” site:edu filetype:.pdf
- “region adjacency graphs” site:edu filetype:.pptx

### STATS Sample Queries
- “linear regression” site:rubikscode.net filetype:.html
- “hypothesis testing” site:edu filetype:.pdf
- “heteroscedasticity” site:edu filetype:.pptx
- “random event” site:paperswithcode.com filetype:.html
- “maximum likelihood” site:edu filetype:.pdf
- “granger causality” site:edu filetype:.pptx
- “probability” site:hackernoon.com filetype:.html
- “random sampling” site:edu filetype:.pdf
- “correlation coefficient” site:edu filetype:.pptx
- “chi-squared statistic” site:skymind.ai filetype:.html

#### Table 2: Sample queries in the three domains.

| Query Num | NLP | CV | STATS | Total |
|-----------|-----|----|--------|-------|
| Pos.Num   | 9,589| 11,101| 6,742  | 27,432|
| Pos.Rate  | 0.6169| 0.8034| 0.6501 | 0.6905|

#### Table 3: Dataset statistics by domain and file type. **Pos.Num** is the number of positive resources. **Pos.Rate** is the fraction of resources that were labeled as positive.

2.2. Feature Extraction
To train a classifier to identify high-quality educational resources, we first focus on feature engineering. Specifically, we investigate three groups of classification features and summarize them in Table 5.

**Group 1 Features** Some of the meta-features of a document that can characterize its quality are embedded in its structure. The features encompassed by Group 1 are high-level and coarse-grained, and focus on aspects...
such as: the number of headings, equations, outgoing links and authors. Heuristically, some good tutorials may tend to include more equations and paragraphs (longer content). We list all 8 such features in Table 5, Group 1.

Group 2 Features These meta-features describe the fine-grained but statistical details of the resource document. The URL’s components, such as the top-level domain name and subdomain name, correlate resources from websites that deliver consistent quality. The other Group 2 features are centered around the characteristics of the free text. For instance, NormalizedUniqueVocab (the size of the vocabulary divided by the total number of words) can estimate the vocabulary’s complexity, and PercentTypos (the percentage of words that are incorrectly spelled) can approximate reliability. We itemize such features in Table 5, Group 2.

Group 3 Features The above features are intuitive and statistical features selected by feature engineering. In addition, we introduce contextualized semantic features with pretrained language models as Group 3 features. To achieve this, we choose three base models: BERT (Devlin et al., 2019), SciBERT (Beltagy et al., 2019) and Longformer (Beltagy et al., 2020). BERT is a language model that was pretrained on Wikipedia documents. SciBERT is a BERT-based model trained in the scientific domain, making it suitable for our use case. Longformer is a BERT-based model that handles longer input sequences.

We introduce a novel pretraining approach: QD-MLM (Query-Document Masked Language Modeling) to leverage these base models to generate features for our classification task. The model takes a query term and a corresponding document text as an input pair. A query term could be a single word, phrase or a paper title, indicating the topic or main idea of the document. The pretraining approach is a following of the Masked Language Modeling (MLM) method of BERT (randomly masking 15% tokens and letting the model predict them), as shown in Figure 2. To conduct QD-MLM pretraining, we apply two external educational corpora for pre-training to ensure the data quality: TutorialBank (TB) and arXiv. The latest TutorialBank has 15,584 topic-document pairs; and arXiv has 259,050 title-abstract pairs (computer science papers only). We enumerate all models in Table 5, Group 3, naming dataset_modelname. We end up with 9 features in Group 3.

After pretraining, the model serves as an encoder for any input documents. However, one may notice that this gives dense embeddings, making it hard to combine with explainable Group 1 and 2 features. Thus, we propose an information retrieval-based scoring function to transfer dense embeddings into a score feature. This scoring function calculates a score for each retrieved document.
source, showing the relevancy of the resource to all the searching queries. Relevancy is one of the most important indicators that the resource is annotated as positive. The score is higher if it is more relevant to the queries. In Section 2.1.1, we apply a list of queries \( q \in Q \) to download resources, we now compute a cosine-similarity based ranking score \( score_r \) for resource \( r \):

\[
    score_r = \sum_{q \in Q} \cos(V_q, V_r)
\]

where \( V_q \) and \( V_r \) are QD-MLM encoded embeddings for the query term and resource respectively.

### 2.3. Resource Classification

We treat NLP as the source domain, and CV and STATS as two target domains, given the fact that there are more resources in NLP. So we study two experimental settings: NLP\( \rightarrow \)CV and NLP\( \rightarrow \)STATS. Since there are various feature types, we conduct pre-processing before applying the classifiers. Numerical values are binned into groups, and categorical features are converted into integer codes. We evaluate four traditional classifiers: Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM) and Logistic Regression (LR). We find that RF performs the best and has a slight edge over DT, but SVM and LR significantly lag behind. Thus, we report the Random Forest’s performance, summarized in Table 6. Specifically, we include precision, recall and F1 scores on different feature groups: Group 1, Group 1+2, and Group 1+2+3. It shows that with more features included, better performance can be obtained. When we include all feature groups, we can achieve the best F1 score in both target domains. In general, performance on the CV domain is better than on STATS. This is expected given that the corpus distance between NLP and CV is smaller than between NLP and STATS. We give detailed data analysis in the next section.

### 3. Data Analysis

To better understand the collected data and our classifier’s performance, we conduct a study on the feature analysis and domain differences. Finally, we also compare similar existing datasets.

#### Feature Importance Score

We take the best-performed model of NLP\( \rightarrow \)CV domain (Group 1+2+3), and take the Gini Index calculated by Decision Trees as the feature importance score. Overall, we extract 8746 features in CV and 8525 features of STATS after binning numerical values and encoding categorical features. In Figure 3, we list the top 20 features of CV and STATS. Some Group 1+2 features rank in the top 5, since they are main indicators that the resource is informative (i.e., more heading numbers, longer contents). Some heuristic features such as sentence, word and bibliography lengths rank in the top 20. This observation validates our assumption that such features may indicate more informative content and tend to be a positive resource. Additionally, Group 3 features (marked with shaded color) also play an important role. In fact, all Group 3 features rank top 20, suggesting that our scoring function that applies QD-MLM semantic features into the pipeline is very helpful when doing classification for resource discovery.

#### Domain Differences

As observed before, our transfer learning pipeline performs better on CV than on STATS, and this can be attributed to domain differences relative to the source domain NLP. In Figure 4, we plot the percentage of overlapping n-grams of both \{NLP, CV\} and \{NLP, STATS\} domain pairs. This indicates that NLP and CV have a larger overlap than \{NLP, STATS\} with respect to all of the n-grams \( n \in \{1, 2, 3, 4\} \). For example, NLP and CV share nearly 80% on 2-gram, while NLP and STATS share only about 50%. From this perspective, we uphold that the classifiers trained on semantic features based on BERT models are valuable for bridging more distant domains with transfer learning.

To further contrast our findings, we enumerate the top 10 URLs in Table 7. Although the websites are ranked in different orders, there are still common URLs across the domains (highlighted in the table). Once again, CV shares more overlap with NLP in comparison to STATS. Along with the feature importance score, this cross-domain consistency further illustrates that the URL meta-features will benefit our model’s out-of-domain classification.

#### Comparison with Similar Datasets

We compare a number of existing NLP-related educational datasets...
Table 6: Classification Results in two target domains: CV and STATS.

| Domain | NLP→CV | NLP→STATS |
|--------|--------|-----------|
| Features | F1 | Precision | Recall | F1 | Precision | Recall |
| Group 1 | 0.7238 | 0.5802 | 0.9617 | 0.6508 | 0.5405 | 0.8177 |
| Group 1 + 2 | 0.8579 | 0.7772 | 0.9571 | 0.7990 | 0.8141 | 0.7845 |
| Group 1 + 2 + 3 | **0.9402** | 0.9849 | 0.8994 | **0.8225** | 0.9965 | 0.7002 |

Table 7: Comparison of the top 10 sites. Gray means overlapped in both CV and STATS domain; Purple means overlapping between NLP and CV; Blue means overlapping between NLP and STATS.

4. Application: Leading Paragraph Generation for Surveys

This section demonstrates an interesting application that applies the resources discovered using our ERD Pipeline: leading paragraph generation for surveys using web data. Novel concepts are being introduced and evolving at a rate that creates high-quality surveys for web resources, such as Wikipedia pages, challenging. Such existing surveys like Wikipedia still need human efforts on collecting relevant resources and writing accurate content on a given topic. Survey generation is a way to generate concise introductory content for a query topic (Zhao et al., 2021). While most of the existing work focuses on utilizing scientific papers or Wikipedia to achieve this goal, little has been done for using the data on the web. Since our ERD pipeline discovers sufficient web data, we propose a two-stage approach for generating the lead paragraph that applies these web data. Notably, this is the first research on abstractive survey generation using web data.

4.1. Two-stage method

We propose a two-stage method illustrated in Figure 5. Given a query topic and high-quality web resources selected by the ERD pipeline, we wish to generate the leading introductory paragraph for the query topic. This approach consists of content selection (step 1) and abstractive summarization (step 2). Content selection is the process of selecting the most relevant sentences according to the given query. Abstractive summarization generates the accurate lead paragraph from the selected sentences.

**Content Selection** ERD is supposed to identify mas-
sive resources with broad coverage of the topics, so the first step is to select related content with the query topic.

While there is no suitable pretrained data for this survey generation task, we utilize the WikiSum dataset (Liu et al., 2018). WikiSum contains 1.5 million Wikipedia pages, their references and their associated Google Search results. WikiSum includes many well-established topics and comprehensive reference documents, making it suitable for survey generation. We first evaluate content selection models using WikiSum. We experiment with three approaches in this step. Liu and Lapata (2019) undertake query-based content selection as a regression problem of predicting the ROUGE-2 recall of a given paragraph-topic pair (LSTM-Rank). Reimers and Gurevych (2019) fine-tune BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) to produce fixed-length vectors which can be compared using cosine similarity. We embed the topic of each Wikipedia page and candidate paragraph using this method, and select the paragraphs with the closest vectors to the title (Semantic Search). Additionally, we train RoBERTa in a similar manner as (Liu and Lapata, 2019). Then, we compare the query topic and paragraphs as sentence pairs and use the resulting relevance scores for the paragraph ranking (RoBERTa-Rank). As shown in Table 9a, RoBERTa-Rank is the highest-scoring content selector, so we employ it for the abstractive summarization’s input.

**Abstractive Summarization** This step is to generate summarization from the content selected previously. As a sequence-to-sequence task, there are many existing pretrained models. We experiment with BART (Lewis et al., 2019), a pretrained model for text generation, as well as HierSumm, a hierarchical model from Liu and Lapata (2019). We show the summarization results on the WikiSum data in Table 9b and observe that BART achieves a better performance.

### 4.2. Human Evaluation and Case Studies

So far, we have shown that applying RoBERTa-Rank and BART as a two-stage method gives promising results evaluated on the WikiSum dataset. We connect our pipeline with this method to generate the leading paragraph. We choose ten queries randomly as survey topics in each domain, for example, “sentiment analysis” in NLP. A complete query topic list can be found in Table 11. Since we do not have ground truth, we conduct human evaluation and case studies.

We evaluate the model outputs on a 1-5 Likert scale based on the following qualities:

- **Readability**: attains a maximum score of 5 if the output is readable with a high degree of fluency and coherency.
- **Relevancy**: attains a maximum score of 5 if the output is perfectly relevant to the current topic with no hallucinations.

**Table 10: Human Evaluation**

| Evaluation | NLP | CV | STATS |
|------------|-----|----|-------|
| Avg. Readability | 3.45 | 2.90 | 2.75 |
| Avg. Relevance | 2.80 | 1.85 | 1.50 |
| Avg. Non-redundancy | 2.45 | 2.15 | 1.60 |

**Table 11: Topics selected for human evaluation.**
In computer science, knowledge graphs are a type of graphical representation of information about a system. Knowledge graphs are used in computer science to describe the structure of a system, such as a graph of knowledge about a particular system, or a list of items that can be used to describe a system’s structure. For example, a knowledge graph may contain information about an object’s shape, its size, its shape relative to other objects, its orientation, and its orientation relative to a point in space, or its position relative to another point in time, or any combination of these things. Knowledge Graphs can also be used as a way of describing the structure and structure of systems, such that a system can be described by a set of knowledge graphs that describe its structure and its properties.

In computer science, a Convolutinal neural network is a type of neural network used in image analysis and image synthesis. It is a computer program that uses a neural network to learn from a large number of images, and can be used to predict the appearance of a given image in real-world situations, such as the shape of a surface, or the color of an object in a 3D environment such as an image of a person’s face. It can also be used for image synthesis and image analysis, as well as image processing and image processing for computer vision and image recognition. It has been used in a number of applications such as computer vision, image processing, image recognition, and computer vision for image recognition and image rendering.

### 5. Conclusion

In this paper, we proposed a pipeline for automatic knowledge discovery in novel domains. We applied transfer learning with an MLM pre-training method and achieved competitive classification performances. We demonstrated an application to take advantage of resources discovered by our pipeline. Finally, we released our source code and the collected datasets, including the 39,728 manually labelled web resources and 659 search queries. We make this pipeline an online live educational tool for the public.

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### Table 12: Examples of generated leading paragraphs.

| Topic | Example |
|-------|---------|
| NLP: knowledge graphs | Knowledge graphs are used in computer science to describe the structure of a system, such as a graph of knowledge about a particular system, or a list of items that can be used to describe a system’s structure. For example, a knowledge graph may contain information about an object’s shape, its size, its shape relative to other objects, its orientation, and its orientation relative to a point in space, or its position relative to another point in time, or any combination of these things. Knowledge Graphs can also be used as a way of describing the structure and structure of systems, such that a system can be described by a set of knowledge graphs that describe its structure and its properties. |
| CV: image retrieval | In computer science, a Convolutional neural network is a type of neural network used in image analysis and image synthesis. It is a computer program that uses a neural network to learn from a large number of images, and can be used to predict the appearance of a given image in real-world situations, such as the shape of a surface, or the color of an object in a 3D environment such as an image of a person’s face. It can also be used for image synthesis and image analysis, as well as image processing and image processing for computer vision and image recognition. It has been used in a number of applications such as computer vision, image processing, image recognition, and computer vision for image recognition and image rendering. |
| STATS: normal distributions | In physics, normal distributions are a family of mathematical models that describe the distribution of normal distributions. They are used in the fields of statistics, physics, and computer science, and have been used in a wide variety of applications, including computer vision, image analysis, computer graphics, computer vision, computer graphics processing units (CPGs), as well as in the field of computer vision. They have also been used to study the visual appearance of real-world surfaces, such as the Phong Reflection Model, the Oren-Nayar model, the Koenderink et al. representation, and the Shading of the Sphere Model, and in the study of light sources and light sources in OpenGL and OpenGL-based graphics renderers. |

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*Non-redundancy*: attains a maximum score of 5 if the output has no repeating phrases/concepts.

We report average scores among 2 human judges of all topics by domain, shown in Table 10. The scores of NLP are the highest for all qualities, and STATS performed most poorly. This discrepancy may be caused by data collection bias, as more NLP resources were included. We randomly pick one case study from each domain in Table 12. We eliminate some parts of the generated content due to limited space. The model is able to generate leading paragraphs in a similar Wikipedia article style by giving a definition of a certain concept, following by descriptions of possible applications. Overall, while these surveys contains some facts, the quality can still be improved. For instance, the STATS paragraph exhibits some repetition and redundancy. Overall, while these surveys contains some facts, the quality can still be improved. For instance, the STATS paragraph exhibits some repetition and redundancy. Overall, while these surveys contains some facts, the quality can still be improved. For instance, the STATS paragraph exhibits some repetition and redundancy.
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