FEE.org Content Recommendations & Visitor Analysis

David Veksler





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The problem

Who are our visitors?

- What content engages users?
- What does a typical session look like?

Can we improve engagement?

Can we push relevant content to visitors?

Solution

Build content recommendation algorithm

Analyze the content and suggest related content to users.

Process

Extract metadata

Build script which extracts all content from the CMS

Extract features

Convert all text fields in each article to a term frequency—inverse document frequency feature matrix

Find related content

Given a URL, return 5 similar articles

Part 2: Content & Visitor Analysis

https://github.com/DavidVeksler/DS3-Projects/blob/master/Final%20Project/Part%203%20-%20 Exploratory%20Analysis.ipynb

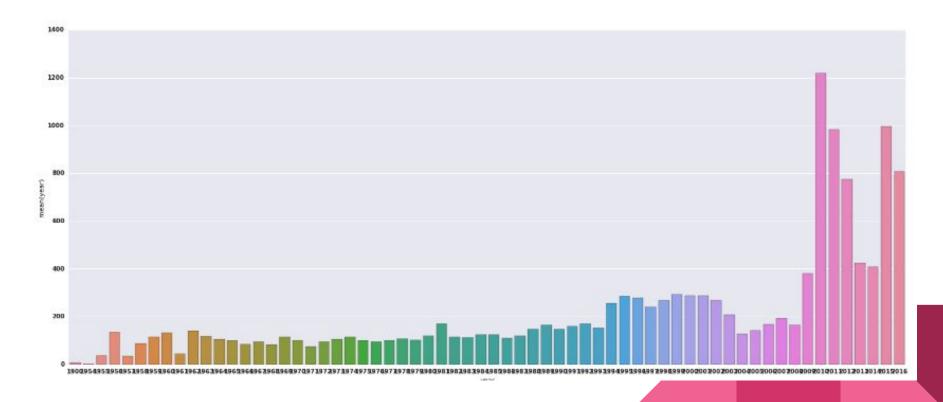
Content Analysis

- 13000 articles over 66 years
- Source: content management system

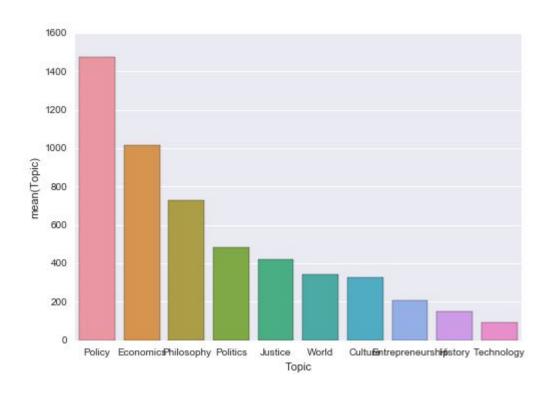
Visitor Analysis

- 50,000 actions (page views) over 11 hours
- Source: Clicky web traffic logs

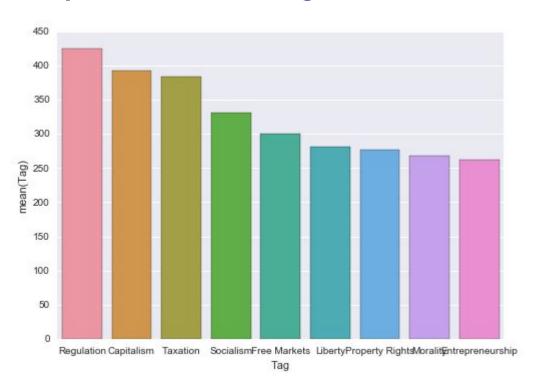
Articles per year, 1952-2016



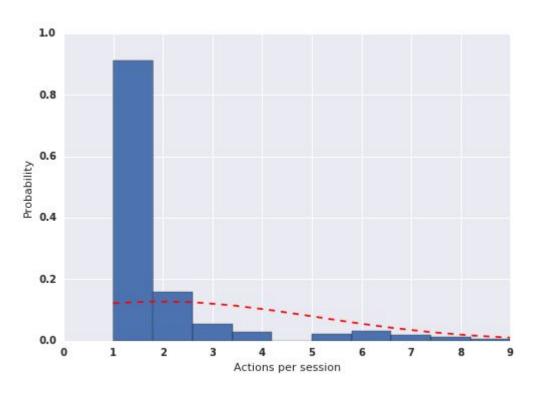
Top Categories



Top Editorial Tags



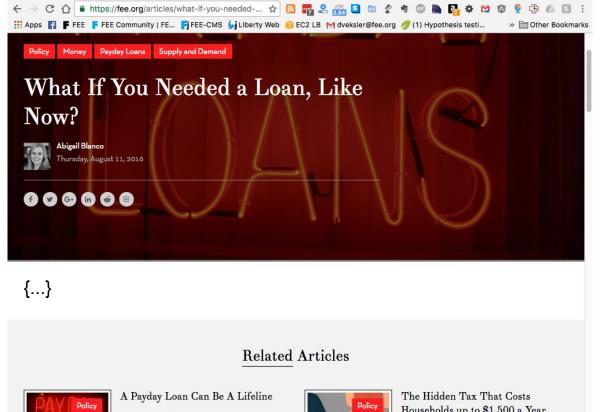
Actions per session



Top Referring domains



Part 2: Similar Article Recommendations





Paige Marta Skiba - June 07, 2016

O Comments



Households up to \$1,500 a Year

Salim Furth - April 18, 2016

3 Comments



9 Ways Austin Blocks New Housing in Central City

Dan Keshet - April 07, 2016





Feds' Crazy Plan: Make Risky Loans, Don't Charge for Them

Ike Brannon - March 17, 2016



0 Comments

Step 1: Extract all text fields & URLs

- Build command-line interface to Umbraco Content Management System
- 2. Strip HTML.
- 3. Encode text to JSON.
- Extract all values to a CSV file.

```
var articles = access.Services.ContentService.GetChildren((int)CmsTopLevelContentNodes.Articles);
var metas = new List<ArticleMetadata>();
    articles.ForEach(article =>
    {
        Console.WriteLine("{0}: {1}", article.Name, article.ToString());
        metas.Add(GetArticleMetadata(article));
    });
    WriteMetaDataToFile(metas);
```

Pre-process CSV to Pandas Pickle

- Convert CSV to Pandas DataFrame
- 2. Parse dates and convert tag to list.
- 3. Decode JSON strings
- 4. Strip HTML from content from html.parser import HTMLParser
- 5. Save DataFrame to Pandas pickle data.to_pickle('assets\dataset\ArticleMetadata.pkl')

```
import pandas as pd
import json

articles = pd.read_pickle('ArticleMetadata.pkl')
articles.DatePublished = pd.to_datetime(articles.DatePublished)
articles.Tags = articles.Tags.map(lambda x: str(x))
articles.TagArray = articles.Tags.map(lambda x: x.split(','))
articles.TagArray[0]
articles.head(1)
```

	Url	Title	Tags	Topic	DatePublished	Abstract	FullText
ArticleId				9			
12897	/articles/amc-s- halt-and-catch- fire-is-capital	AMC's "Halt and Catch Fire" Is Capitalism's Fi	Capitalism, Competition, Property Rights, Entrepr	Economics	2015-09-02 10:56:24	"The show is a vibrant look at the early PC in	"AMC's Halt and Catch Fire is a brilliant

Step 3: TfidfVectorizer

1. Extract words as features with TfidfVectorizer

from sklearn.feature_extraction.text import TfidfVectorizer

tfidf = TfidfVectorizer(stop_words='english',min_df=3).fit_transform(articles.RawText.dropna()) # no need to normalize, since Vectorizer will return normalized tf-idf pairwise similarity = tfidf * tfidf.T

Step 4: Compute Cosine Similarity

1. Compute the linear kernel between X and Y.

from sklearn.metrics.pairwise import linear_kernel

```
def FindSimiliarArticles(url, tfidf_matrix, articles):
   matches = articles.loc[articles['Url'] == url].index.tolist()
   originalArticleIndex = int(matches[0])
   print("original index: %s" % originalArticleIndex)
   cosine_similarities = linear_kernel(tfidf_matrix[originalArticleIndex], tfidf_matrix).flatten()
   print("cosine_similarities: %s" % cosine_similarities)
   related_docs_indices = cosine_similarities.argsort()[:-5:-1]
   print('related articles: ' % related_docs_indices)
   related_articles = []
   [related_articles.append(articles.iloc[index]) for index in related_docs_indices]
   return related_articles
```

Demo

related = FindSimiliarArticles('/articles/how-america-can-keep-the-entrepreneurs-we-train/',tfidf,articles) print(related)

Original index: 13795

cosine_similarities: [0.05772269 0.04216487 0.04971372 ..., 0.00795316 0.03272186 0.024919] related articles:

Url /articles/how-america-can-keep-the-entrepreneu...

Title How America Can Keep the Entrepreneurs We Train

Name: 13795, dtype: object, ArticleId 132805

Url /articles/immigrants-are-twice-as-likely-to-st...

Title Immigrants Are Twice as Likely to Start a Busi...

Name: 671, dtype: object, ArticleId 108006

Url /articles/why-government-jobs-programs-destroy...

Title Why Government Jobs Programs Destroy Jobs

Name: 1076, dtype: object, ArticleId 129584

Url /articles/5-charts-that-show-trumps-immigratio...

Title 5 Charts that Show Trump's Immigration Paper I...

Name: 338, dtype: object]

Part 3: Other Classifier & Clustering Experiments

Other experiments:

- Keyword modeling with Word2Vec Neutral Network
 - Useful for tag recommendations.
- Document clustering K means
 - o Incomplete, too complex
- Topic modeling with latent Dirichlet allocation
 - Not very good results

```
In [12]: num_topics= 10
         num words per topic= 10
         for ti, topic in enumerate(lda model.show topics(num topics,num words per topic)):
             print("Topic:
                                 %d" % (ti))
             print(topic)
             print()
         Topic: 0
         (0, '0.001*government + 0.000*tax + 0.000*people + 0.000*moore + 0.000*tubman + 0.000*soto + 0.
         *education + 0.000*trade + 0.000*new + 0.000*economic')
         Topic: 1
         (1, '0.001*government + 0.001*venezuela + 0.001*market + 0.001*free + 0.001*state + 0.001*madur
          0.001*erhard + 0.001*economic + 0.001*jury + 0.001*amazon')
         Topic: 2
         (2, '0.002*government + 0.002*people + 0.002*market + 0.001*economic + 0.001*world + 0.001*free
          0.001*state + 0.001*new + 0.001*money + 0.001*percent')
```

The End