SABLE: Tools for Web Crawling, Web Scraping, and Text Classification

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Outline

- Motivation
- SABLE Overview
- Applications
- Moving to a Production Environment
- Quality
- Future Work

Motivation

- For many economic surveys, respondent data or equivalent-quality data are available online
- Respondents sometimes direct Census Bureau analysts to their websites to obtain data
- Going directly to online sources and collecting data passively could reduce respondent and analyst burden
- For the most part, current data collection efforts along these lines are manual

Goal

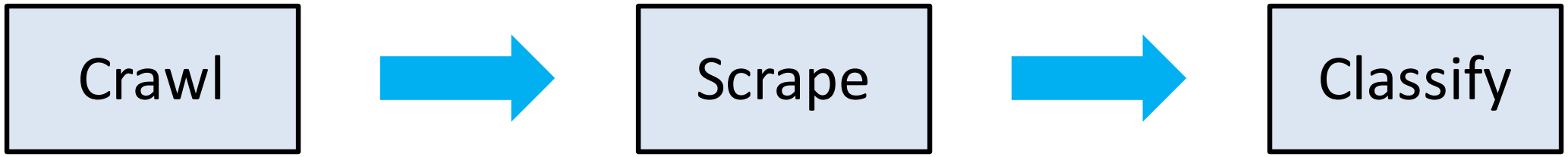
Automate the process of finding, scraping, and organizing data from online sources

- Challenges
  - Websites and the documents on them lack standardization
  - Data are often in formats not amenable to analysis right away such as Portable Document Format (PDF)

What is SABLE?

- Scraping Assisted by Learning
- Collection of tools for
  - Crawling websites
  - Scraping documents and data
  - Classifying text
- Models based on text analysis and machine learning
- Implemented using free, open-source software
  - Apache Nutch
  - Python

Three Main Tasks



Given a website,

- Scan website
- Find documents and extract text
- Apply classification model to predict whether document contains useful data

Given a document classified as useful,

- Apply model to learn the location of useful data
- Extract numerical values and corresponding text

Given scraped data,

- Preprocess data
- Apply classification model to map text to Census Bureau definitions and classification codes

Machine Learning

- In some applications, machine learning is used to classify text
- Examples of text classes
  - Document is “Useful” or “Not Useful”
  - Census Bureau classification codes
- Machine learning models pick up on associations between word sequences and classes
- Building a training set on which to fit models is manually intensive and usually time-consuming

Training Set

Document Text	Feature for "tax"	Feature for "revenue"	...	Feature for "tax revenue"	True Class
tax revenue for local governments	1	1		1	Useful
state government tax collections	1	0		0	Useful
instructions for filling out tax form	1	0		0	Not Useful
retirement announcement	0	0		0	Not Useful
tax revenue statistical abstract	1	1		1	Useful
upcoming road closures	0	0		0	Not Useful

Test Set

Document Text	Feature for "tax"	Feature for "revenue"	...	Feature for "tax revenue"	True Class	Predicted Class
parks and recreation guide	0	0		0	Not Useful	?
local government tax collections	1	0		0	Useful	?

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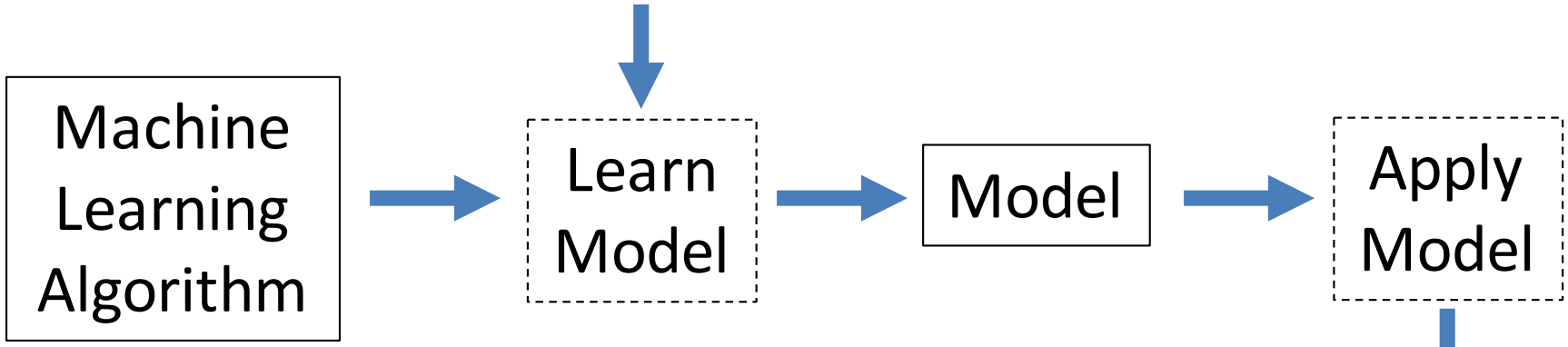

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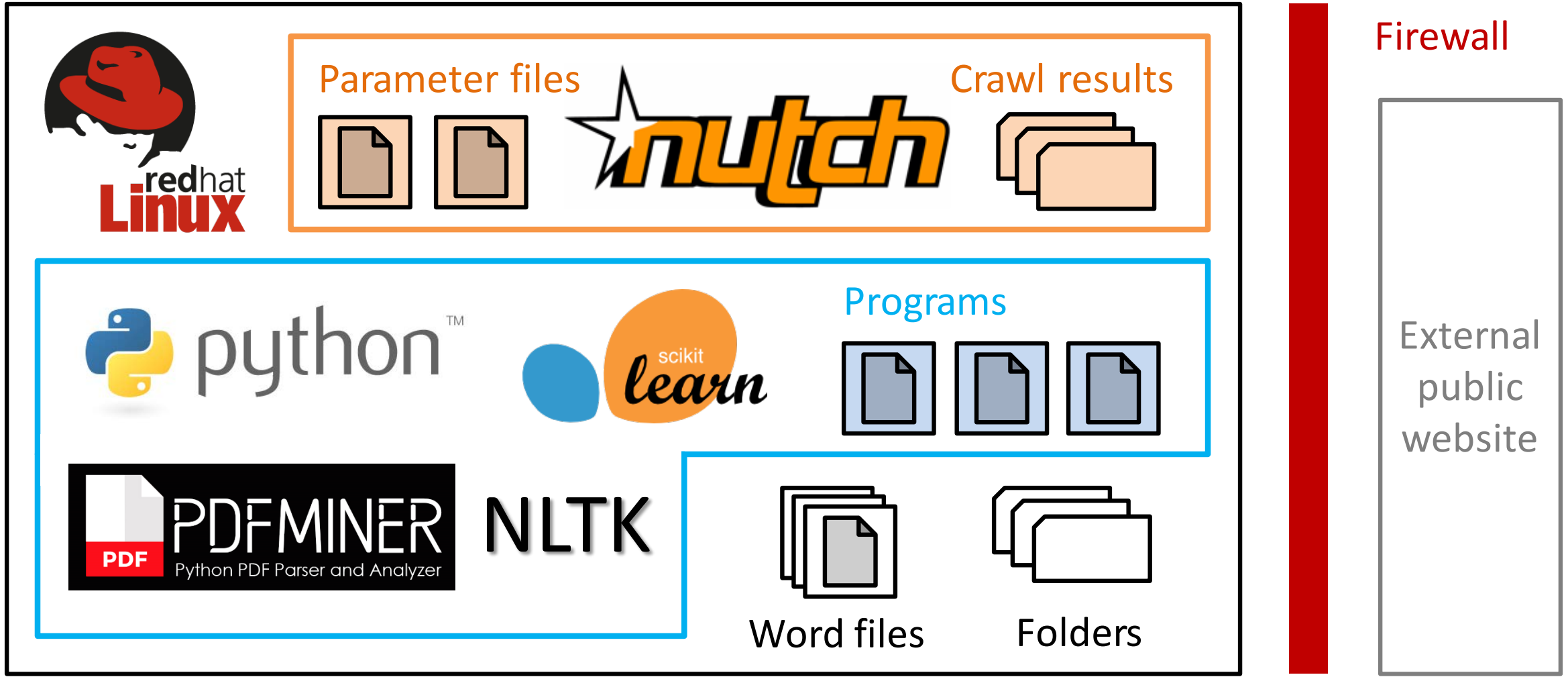
Note: Adapted from Introduction to Data Mining (Tan, Steinbach, and Kumar; 2006; p. 148). Accessed February 2, 2018. Available online at https://www-users.cs.umn.edu/~kumar001/dmbook/ch4.pdf

Architecture Design



Applications and Research Areas

- Public sector projects
  - Find new sources of tax revenue collection statistics on government websites
  - Scrape pension statistics from specific Comprehensive Annual Financial Reports (CAFRs)
- Autocoding and write-ins
  - Assign North American Industry Classification System (NAICS) codes to establishments based on business descriptions for the Economic Census

Tax Revenue Statistics

- Data on state government tax revenue collections can be found online in CAFRs and other publications
- Used SABLE to find additional online sources
  - Crawled websites of state governments
  - Discovered approximately 60,000 PDFs
  - Manually classified a random sample of 6,000 PDFs as “Useful” or “Not Useful”
  - Applied machine learning to build text classification models based on occurrences of word sequences

Pension Statistics

- Likewise, data on public pension funds can be found online and in CAFRs
- Examine feasibility of scraping data
- Pension statistics
  - Service cost
  - Interest
- Two-stage approach
  - Identify tables using occurrences of word sequences
  - Apply scraping algorithm based on table structure

REQUIRED SUPPLEMENTARY INFORMATION – PENSION

CHANGES IN NET PENSION LIABILITY

	Fiscal Year Ended		
	2016	2015	2014
Total pension liability			
Service Cost (MOY)	$ 71,218,683	$ 70,056,133	$ 66,696,324
Interest (includes interest on service cost)	241,733,937	231,804,221	220,238,560
Differences between expected & actual experience	(31,199,454)	(27,900,755)	-
Benefit payments, including refunds of member contributions	(146,657,716)	(137,771,219)	(131,100,585)
Net change in total pension liability	135,095,450	136,188,380	155,834,299
Total pension liability - beginning	3,260,156,781	3,123,968,401	2,968,134,102
Total pension liability - ending	3,395,252,231	3,260,156,781	3,123,968,401

Source: Comprehensive Annual Financial Report For Fiscal Years Ended June 30, 2016 and 2015; Santa Barbara County Employees' Retirement System; A Pension Trust Fund for the County of Santa Barbara, California
< http://cosb.countyofsb.org/uploadedFiles/sbcers/benefits/SBCERS%206-30-2016%20CAFR%20With%20Letters.pdf >

Autocoding and Write-ins

- The Census Bureau classifies business establishments according to NAICS
- Information for classification comes from various sources such as write-in responses to the Economic Census
- Disadvantages of assigning NAICS codes manually
  - Expensive
  - Time-consuming
  - Introduce systematic errors
- Use text classification models developed in SABLE to automate assignment of NAICS codes

NAICS Classification Example

Business Description Paintball Field, Supplies, & Games

Standardized Text: paintball field supplies games

1-Word Sequences: “paintball”, “field”, **“supplies”**, **“games”**

2-Word Sequences: **“paintball field”**, “field supplies”, “supplies games”

Sporting Goods Stores 45111026

All Other Amusement and Recreation Industries 71399080

Moving to a Production Environment

- Approval to use Apache Nutch 1.13
- Two Linux servers
  - Development
  - Production
- Authority to Operate (ATO)
- SABLE repository on the Census Bureau's GitHub account
  - https://www.github.com/uscensusbureau/SABLE
  - Programs, supplementary files, and documentation

Quality

- Integrate quality into SABLE early on
- Establish procedures for assessing quality on a regular basis
- Crawling and scraping
  - Manual checks
  - Comparisons with respondent data
- Machine learning
  - Recruit subject matter experts to help create training sets
  - Assess quality of predictions and identify and quantify different misclassification costs

Future Work

- Obtain Authority to Operate
- Update SABLE GitHub repository periodically
- Create a data product based on scraped data
- Research how to assign North American Product Classification System (NAPCS) codes based on product descriptions for the Economic Census

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