# Researcher Homepage Identification and Name Extraction

Application of Machine Learning with Multiple Views

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#### Introduction

- Topic: The implementation and assessment of a machine learning approach for the information extraction from web pages.
- Motivation: Automated means of gaining insights from the web; an enormous collection of semi- and unstructured data.
- Method: Supervised Machine Learning Binary Classification

#### Typical Researcher Homepage



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Homepage Identification as Supervised Machine Learning Task

#### Supervised Learning

For a collection of data points  $\langle (x_i, y_i) \rangle_{i=1}^N$ , learn a function  $h: x \to y$ , which predicts the label  $y_{N+1}$  for a new datapoint  $x_{N+1}$ .

- Number of datapoints N, which were collected in the past  $x_i \in \mathbb{R}^D$
- $y_i \in \{true, false\}$

• 
$$h(x_{N+1}) = P(y_{N+1}|x_{N+1})$$



Boedecker et al. (2017)

## Questions?

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#### The Main Tasks

- Obtain suitable web page data
- 2. Identify researcher homepages
  - Develop two prediction models using disjoint feature sets
  - Bag of words approach
- 3. Extract the researchers name from the page
  - Extract all person names from the homepage
  - Identify the correct person name
  - Augmenting heuristic with machine learning features

## Common Crawl

- Non profit organization that crawls the web on a monthly basis
- Crawl data is stored in Amazon Web Services as part of their Public Datasets Program
- Approx. 300 index files per crawl. ( $\sim 1.5$  TiB uncompressed)
- Crawl of August 2019: 260 TiB (uncompressed), 2.95 billion web pages



#### URL Based Features - URL Surface Patterns<sup>1</sup>

- https://www.inf.uni-hamburg.de/en/inst/ab/hci/news/rse15.html nondict, nondict, nondict, news, alphanumeric
- (2) http://abi.inf.uni-tuebingen.de/People/krueger people, nondict
- (3) http://people.ucas.ac.cn/~zhangxiaopeng?language=en tildenondict, querykeylanguage, queryvaluenondict

#### Surface Patterns:

- numeric, alphanumeric, hyphenated, underscored, long term
- nondict : No proper English word or not in the term dictionary
- $\blacksquare$  tildenondict : Reseacher name prefixed by  $\sim$
- querykey, queryvalue : prefix to URL query terms

<sup>1</sup>Gollapalli et al. (2015)

### **URL Based Features**

- Natural language specific preprocessing applied
- Uni- and bigrams
- Vectorized via Term Frequency Inverse Document Frequency (Tfidf)

Url_Id	tildenondict	numeric	querykeyid		news	people	Label
0	0.723131	0	0		0	0.160545	1
1	0	0.983265	0.324515		0	0	0

Each row represents a web page and is a sparse vector of 8386 features.

## Page Content Based Features

- Text from title and h1 tag prefixed with identifier
- Concatenated with the rest of the page text content
- Numeric Features:
  - Num. tables
  - Num. external links
  - Num. internal links
  - Num. images
  - Num. person names in title / h1 tag

Features after preprocessing: 20006 Tfidf vectorized uni-, bi- and tri-grams

## Machine Learning Models

Random Forest and linear models with Stochastic Gradient Descent learning were compared.

Best URL based model:

- Random Forest
- Default parameters except for number of trees (1000)

Best Page Content based model:

Support Vector Machine with modified huber loss function

Combined model prediction:

 $P_{combined}(y|x) = P_{url}(y|x) * P_{page}(y|x)$ 

## Questions?

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#### Training Data

Training data downloaded from July, August and September Crawl of 2018.

Source	No. Homepages
World Wide Knowledge Base <sup>2</sup> - 4 Universi-	52
ties Dataset	
Computer Science Bibliography <sup>3</sup>	14 473
Manual Labelling (Freiburg, Munich, Stan-	2130
ford, Media Faculty of the MIT)	
After filtering the html data	13 670

Undersampling was applied to account for imbalanced classes



#### Validation- and Test-Data

Validation Data:

- Cross Validation as part of GridSearch
- Hold out dataset

Test Data:

- 1500 web pages were manually labelled
- Universities: Caltech, Princeton, York, Stuttgart, Hamburg, Applied Science Upper Austria

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Contained 86 homepages



#### Metrics

<u>Precision</u>: Quality of the predictions made by the model. How good are the predictions of the model.

$$\frac{\sum \textit{True Positive}}{\sum \textit{True Positive} + \sum \textit{False Positive}}$$

<u>Recall</u>: Measure for the coverage of the model. How well is the model suited to predict the label.

$$\frac{\sum \textit{True Positive}}{\sum \textit{True Positive} + \sum \textit{False Negative}}$$

<u>F1 Score</u>: Measure of models performance, where precision and recall contribute evenly.

#### Classification Results

		Validation Data			Test Data		
Model	Label	Precision	Recall	F1 Score	Precision	Recall	F1 Score
Page	0	0.97	0.94	0.96	1	0.58	0.73
Content	1	0.94	0.97	0.96	0.12	0.97	0.22
	0	0.91	0.91	0.91	0.99	0.77	0.86
	1	0.92	0.92	0.92	0.18	0.84	0.29
Combined	0	0.95	1	0.97	0.98	0.98	0.98
Combined	1	1	0.94	0.97	0.68	0.69	0.68

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#### Summary

- 68% F1 Score achieved in the homepage identification task
- 94% F1 Score achieved in the person identification task
- Simple machine learning algorithms and features well suited for the web page classification
- Great benefit from using two disjoint feature sets under suboptimal condition
- Convention of writing the researcher name in the title tag is widely held
- Person identification heuristic could be improved with machine learning features

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#### A0: Person Identification - Sampling

- Names extracted with Stanford NE Recognizer, merged and manually labelled
- Training data:
  - Sample taken from the homepage identification training dataset
  - Extracted and labelled 36123 person names from 1705 homepages
- Test data:
  - Sample taken from the homepage identification test dataset
  - Extracted and labelled 2106 person names from 83 homepages

#### A1: Person Identification - The Method

Appendix

$Url_Id$	Name	In_Title	ln_h1	In_h2	Count	Count_Third	Count_Half	No_Parts	Label
0	Name1	0	0	1	5	2	2	1	0
0	Name2	1	1	0	10	3	6	2	1
0	Name3	0	0	0	1	1	1	6	0
1	Name1	1	0	0	16	14	16	2	1

Z-score standardization of numeric features :  $\frac{x_i - \mu}{\sigma}$ 

Machine Learning Algorithm:

Random Forest (250 trees)

#### A2: Person Identification Results

	Validation	Test Data				
Model	Precision	Recall	F1 Score	Precision	Recall	F1 Score
Heuristic	0.93	0.84	0.88	0.95	0.92	0.93
4 Features	0.93	0.92	0.92	0.95	0.93	0.94
All Features	0.96	0.91	0.94	0.95	0.93	0.94



#### **B**: Development Overview



#### Appendix

#### C: Prediction Probabilities by Model and Web Page Type



#### D: Natural Language Preprocessing

- Tokenization : Splitting sequences of characters into useful semanatic units.
- Lower case
- Stopword / Punctuation removal
- Stemming / Lemmatization : Reduce terms to a common base form. (Word Stem / Lemma)
- Term Frequency Inverse Document Frequency (Tfidf):

$$tfidf(t, d) = tf(t, d) \cdot \log \frac{N}{\sum_{D:t \in D} 1},$$

for term t, documents  $d \in D$ , number of documents N.

#### - Appendix

#### E: URL Based Features - 20 Most Frequent Terms by Label



#### F: URL Based Features - Feature Importance

Appendix



# G: Page Based Features - 30 Most Frequent Terms by Label



Feature

#### H: Page Based Features - Feature Importance

- Appendix



#### J: URL Based Model : Common Errors / Improvements

	URL	$P_{url}(y=1 x)$	$P_{page}(y = 1 x)$	Error Type
(1)	http://www-users.cs.york.ac.uk/~susan/sf/dani/PS_019.htm	73	14	
	tildenondict, nondict, underscoredword	.15	.75 .14	
(2)	<ol> <li>https://www.ifm.uni-hamburg.de/en/datenschutz.html</li> </ol>		70	positive
	en, nondict	1	.15	
(3)	https://www.york.ac.uk/economics/our-people/staff-profiles/john-hutton/	37	88	
	economics, hyphenatedword, hyphenatedword, hyphenatedword	.57	.00	
(4)	http://carvermead.caltech.edu/research.html	58	74	false
	research	.30	. / 4	negative

#### Improvements:

Appendix

- (1) Add features representing the beginning and end of the URL.
- (2) Handle non-english terms
- (3) Include meaning of hyphenated terms

#### K: Page Content Based Model : Improvements



2009: Coupled electro-mechanical response of an electroactive polymer cantilever structure and its application in energy harvesting

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Seiteninfo: Impressum | Last Change 1. Mai 2010 by Volkmar Vill und Ron Zenczykowski

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#### Topic Modelling <sup>4</sup>

Substantially expand stopword lists

<sup>4</sup>Gollapalli et al. (2011)

#### Future Work

Improvements:

- Homepage Identification:
  - Training data sampling
  - Individual model feature engineering and feature selection
- Person Identification:
  - Name extraction and name merging procedures at the preprocessing for the person identification
- Overall approach:
  - Co-training<sup>5</sup>
  - Improvements to the probability estimates produced by tree based models<sup>6</sup>

<sup>5</sup>Gollapalli et al. (2015) <sup>6</sup>Tanha et al. (2017)