

A matter of words: NLP for quality evaluation of medical Wikipedia articles

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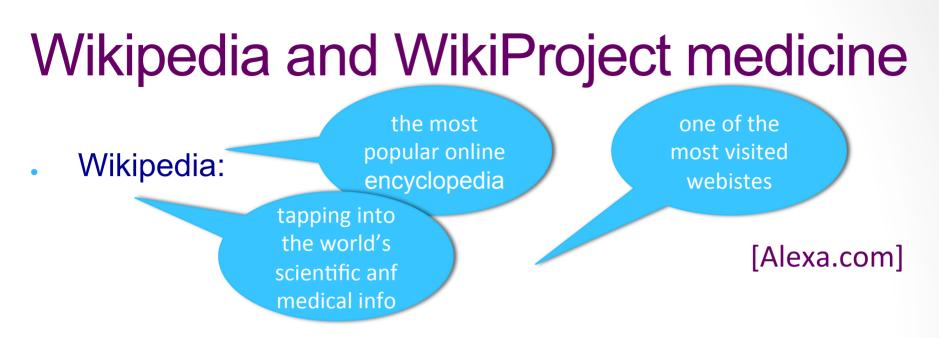


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- Around six out of ten respondents have used the Internet to search for health-related information [Eurobarometer, updated late 2014]
- Wikipedia includes several medical articles under the WikiProject medicine portal
- Wikipedia suffers from trustworthiness issues
- Data quality and appropriate levels of informativeness are even more demanding when health aspects are involved

Wikipedia bots



- Bots act as real users and take care of article creation and editing
- Examples
- <u>User:ClueBot NG</u> reverts vandalism

<u>User:CorenSearchBot</u> – checks for copyright violations on new pages

<u>User:Lowercase sigmabot III</u> – archives talk pages

For a full list: <u>https://en.wikipedia.org/wiki/Wikipedia:Bots</u>

Towards Wikipedia Smart Bots

Automatic quality assessment Vandalism detection Opinion spamming e opinion spammer detection

Guidelines for Quality Assessment

- A number of English Wikipedia articles have been manually evaluated along with a quality label in Wikimedia project
- Guidelines consider linguistic, structural, historical, reputational criteria
- Stub, Start, C, B, A, Good Article (GA), Featured Article (FA)
- GA / FA require a community consensus and a social review by selected editors

Automatic Quality Assessment

• Stvilia et al. (2009):

- linguistic (i.e., Flesch reading-ease score structural, historical and reputational
- ling-ease score

UNSUPERVISED MACHINE LEARNING.

1+1:10

SUPERVISED MACHINE LEARNING.

1+1:10

- clustering and classification to detect FA (90% correctly identified)
- Blumenstock (2008): word count is the most discriminative in identify FA vs others.

Stvilia (2009). A model for online consumer health information quality. JASIST Blumenstock (2008). Size matters: Word count as a measure of quality on Wikipedia. WWW 2008

Baseline: Actionable model

- Actionable Model [Wang 2013], with <u>features</u> related to the content of articles
- The model can also <u>directly suggest strategies for</u> <u>improving</u> a given article quality:
 - Completeness = 0.4*NumBrokenWikilinks + 0.4*NumWikilinks
 - Informativeness = 0.6*InfoNoise + 0.3*NumImages
 - NumHeadings
 - ArticleLength
 - NumReferences/ArticleLength
- Classifiers: Bagging, ADA Boosting, Random Forest

Wang et al.: Tell me more: an actionable quality model for Wikipedia, Wikisym (2013)

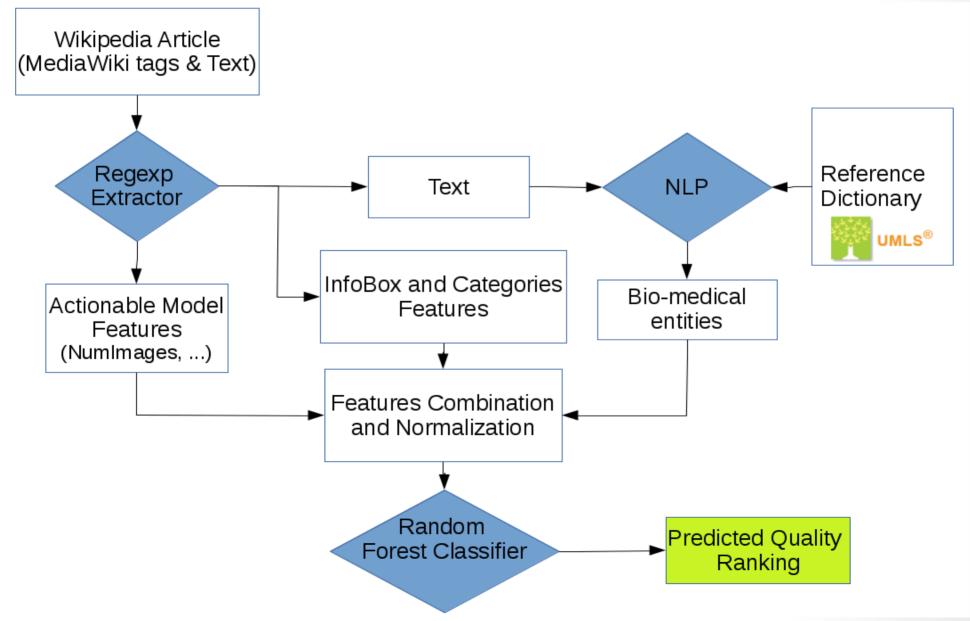
Dataset

class	original dataset	with majority classes sampling	with minority classes oversampling
Stub	9,267	1,015	1,015
Start	9,841	1,015	1,015
C	3,149	1,015	1,015
В	1,894	1,015	1,015
GA	153	153	214
FA	58	58	162
total	24,362	4,271	4,436

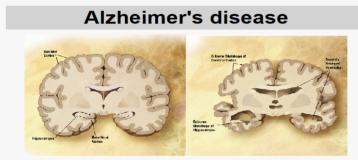
Table 1. Dataset

- Dec. 2014: 24,362 rated documents
- very few (201) articles for FA and GA
- vast majority (19,108) are in the lowest quality classes (Stub and Start)
- we sampled the majority classes
- and oversampled the minority classes
- labeled dataset -> supervised approach

Medical Domain model: Quality Assessment process



InfoBox Feature



Comparison of a normal aged brain (left) and the brain of a person with Alzheimer's (right). Characteristics that separate the two are pointed out.

Classification and external resources

Specialty	Neurology
ICD-10	G30 &, F00 &
ICD-9-CM	331.0 <mark>៤</mark> , 290.1 ៤
OMIM	104300 &
DiseasesDB	490 &
MedlinePlus	000760 &
eMedicine	neuro/13 🗗
Patient UK	Alzheimer's disease 🗗
MeSH	D000544
GeneReviews	NBK1161 교

- Correlation between the quality of an InfoBox and the article quality itself: it's a characteristic featured by GA[1]
- InfoBoxes are strongly correlated to entity types
- InfoboxBoxNormSize is the log10 of the bytes of data contained within the MediaWiki tags that wrap an infobox, normalized to the article length

[1] Krzysztof Węcel , Włodzimierz Lewoniewski. «Modelling the Quality of Attributes in Wikipedia Infoboxes» Business Information Systems Workshops

Categories Feature

- We extracted the article category of interest as:
 - A, when an article is about anatomy;
 - B, when an article is a biography or an event relevant for medicine;
 - D, if it is about a disorder;
 - F, when it is about first aid or emergency contacts;
 - O otherwise

 Categories: Alzheimer's disease
 Ailments of unknown etiology
 Unsolved problems in neuroscience

 Learning disabilities
 Psychiatric diagnosis
 Dementia
 Abnormal psychology
 Cognitive disorders

 Aphasias
 Herpes simplex virus-associated diseases

 Extraction by matching the text within the categories tags with a list of keywords in our categories of interest

catego	ory list of keywords
A	anatom [*] , embryolog [*] , organ, tissue
В	born, death, birth
D	disorder, disease, pathology
F	first aid

D

Domain Informativeness

- Number of bio-medical entities (e.g., symptoms, diseases, treatments, etc.)
- Bio-medical entities extraction:
 - application of NLP analysis to the textual part of the article
 - Adoption of a dictionary-based approach

Bio-medical Entity Extraction 1/3

- Dictionary based approach:
 - A large unlabeled text
 - Preliminary linguistic analysis (sentence splitting, tokenization, lemmatization, Part Of Speech Tagging):
 - UniPi Tanl Linguistic pipeline(*)
 - A reference dictionary

 [1] Attardi, Cozza, Sartiano. «Adapting Linguistic Tools for the Analysis of Italian Medical Records» CLiC-it 2014
 (*)http://tanl.di.unipi.it/en/

Form	Lemma	POS
Other	other	ננ
risk	risk	NN
factors	factor	NNS
include	include	VBP
a	a	DT
history	history	NN
of	of	IN
head	head	NN
injuries	injury	NNS
,	,	,
depression	depression	NN
,	,	,
or	or	CC
hypertension	hypertension	NN

Bio-medical Entity Extraction 2/3

- We created an English medical Thesaurus for medical documents, by extracting definitions from UMLS metathesaurus:
 - •Definition included in SNOMED CT (core terminology for EHR)
 - •Active Ingredients and Drugs from RxNorm
- more than one million entries:



semantic groups	definitions
Treatment	671,349
Sign or Symptom	43,779
Body Parts, Organs, or Organ Components	234,075
Disorder	402,298
Drugs	5,109
Active Ingredients	2,774

Bio-medical Entity Extraction 3/3

- Identification of n-grams, with 1<=n<=10, in a sentence and matching them with definitions in the reference dictionary
 - Exact Match
 - Approximate match:
 - considering the lemmas
 - not considering puntuaction, prepositions and articles

Example

«Other risk factors include a history of head injuries, depression, or hypertension»

Head injuries matches with *head injury* in the dictionary, even if word number differs

Experiments & Results

- 3 models
- Full Medical Domain with ALL NEW features
- Medical Domain with DomainInformativeness
- State of art Actionable Model

		Full	
Baseline	Medical Domain	Medical Domain	Info Gain
ArticleLength	ArticleLength	ArticleLength	0.939
NumHeadings	NumHeadings	NumHeadings	0.732
Completeness	Completeness	Completeness	0.724
NumRef/Length	NumRef/Length	NumRef/Length	0.621
Informativeness	Informativeness	Informativeness	0.377
	DomainInformativ.	DomainInformativ.	0.751
		InfoBoxNormSize	0.187
		Category	0.017

Experiments & Results

- Best results obtained with
- Random Forest Classifier trained with the selected data, wrt 6 quality classes
- 10 cross folder validation

Metric	Baseline	Medical Domain	Full Medical Domain
ROC Area Stub	0.981	0.982	0.983
ROC Area Start	0.852	0.853	0.858
ROC Area C	0.749	0.747	0.76
ROC Area B	0.825	0.832	0.836
ROC Area GA	0.825	0.908	0.916
ROC Area FA	0.977	0.976	0.978
F-Measure Stub	0.886	0.891	0.89
F-Measure Start	0.587	0.582	0.598
F-Measure C	0.376	0.367	0.397
F-Measure B	0.527	0.541	0.542
F-Measure GA	0.245	0.338	0.398
F-Measure FA	0.634	0.631	0.641

Conclusions

- A fine grained classification for all the quality stages of the articles in Wikimedia Medicine Portal.
- *NOVELTY*: NLP techniques for quality assessment.
- Approach adaptable to other languages and other domains
- Full Medical Domain outperforms the baseline for high quality classes, especially GA

Who's Who

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