Classification of Crowdsourced Text Correction

Megha Gupta, Dr. Haimonti Dutta (Advisor)

Second Year Annual Presentation, 2013-2014
IIIT Delhi

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Outline

Courses and TA duties

- Courses (SGPA: 6, CGPA: 7.4)
  MTH 505 - Linear Optimization (4 credits)
- TA duties
  CSE 561 - Probabilistic Graphical Modelling by Chetan Arora

Conferences and Workshops

Conferences

- Presented in ACM India SIGKDD Conference on Data Sciences, Banglore (IKDD CODS, 2015)
- Attended the 3rd International Conference on Big Data Analytics at IIT Delhi (BDA, 2014)

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- System answers to questions like, “What different kinds of corrections are done by users ?” or “What are the most common mistakes made by the OCR device ?”.

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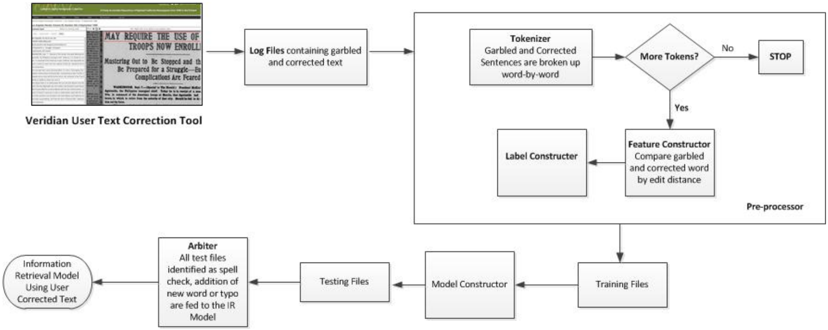
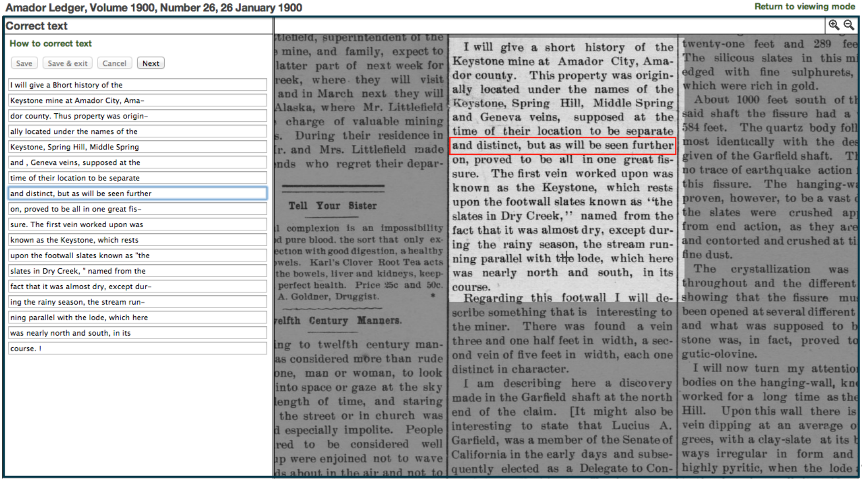
Problem

To build a system for Classification of Crowdsourced Text Correction which takes input as log files containing garbled and manually corrected OCR text, parses and tokenizes them and builds models to categorize the corrections using state-of- the-art machine learning algorithms.

Architecture of the Proposed System



Text Correction Tool



[a]

[a] http://veridiansoftware.com/crowdsourcing/

Datasets [1]

- Raw OCR text (Input)
- Logfiles (Input)
- Corrected OCR Text (Obtained)

[1] https://github.com/megha89/

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  4. Capitalization
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- Information Retrieval Techniques

Results

Table 1 and Table 2 show the Average Loss Error and Average Time taken by the baseline and proposed method using linear and non linear kernels respectively.

Table 1: Results using linear kernel

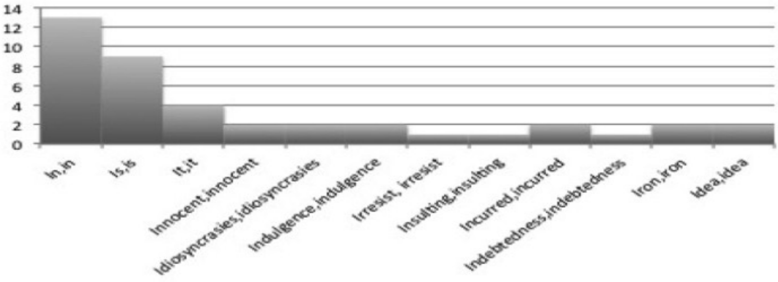
C	AE_b	AE_p	AT_b	AT_p
.0001	99.43±.09	49.47±0.25	1.268±.06	0.11±.01
.1	99.43±.09	49.464±.47	2.512±0.01	0.061±0.01
10	99.43±.09	4.974±.5	2.512±0.01	0.17
1000	99.43±.09	1.743±.14	3.635±0.08	0.382±0.04
10000	99.43±.09	0	6.126±0.02	0.303±0.02

Table 2: Results using polynomial and rbf kernels

C	Polynomial		RBF	
	AE_b	AE_p	AE_b	AE_p
.0001	42±.13	50±.47	63±.15	27±.5
100	42±.13	.33±.2	63±.16	3±.4
1000	42±.13	0±0	63±.16	1.7±.2
C	AT_b	AT_p	AT_b	AT_p
.0001	37±1.4	10±0.2	25±0.7	6±0.2
100	326±11.8	1239±118	540 ± 110	404±34
1000	942±17.4	764±93	537±111.72	957±184

Results contd.

Examples of Capitalization Error, I –> i



Conclusion

- The manually crafted word-level features outperforms the automatically generated char-level features in terms of average loss error.
- The non linear kernels performed better but the time taken by them was marginally high.

Future Work

Though the manually crafted word-level dataset performed better but the time consumed was considerably higher, so there is a need to balance the tradeoff such that the algorithm becomes more compatible with the large scale datasets.

Ongoing Work

Problem: To perform aggregate load forecasting for disparate energy data sources using the ensemble based learning technique called Product of HMMs.

- Motivation

[2] http://redd.csail.mit.edu/

[3] http://open.enernoc.com/data/

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  1. To avoid the unnecessary redundant information thus reducing the network traffic and improving the privacy of the customers.
  2. Efficient power system planning and operation, energy purchasing and generation, load switching and infrastructure development.
  3. Various factors that effect load forecasting are time factors, weather conditions, class of customers, special events, electricity price, fluctuating demand and supply.
- Dataset: REDD[2], IIITD Faculty Housing, Enernoc dataset [3].

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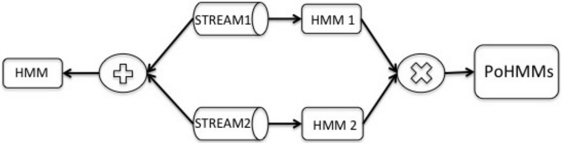
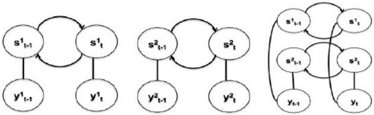
Approach

- Load forecasting at utility level is done in 3 ways:
  1. completely aggregated
  2. completely disaggregated
  3. clustering based approach
- PoHMMs is a model that combines several HMMs by multiplying their individual distributions together and then renormalizing them.



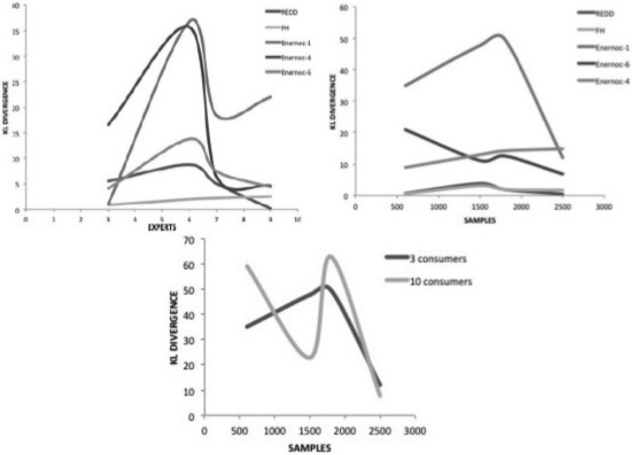
- Each data stream from an appliance is modelled as a HMM/expert with cardinality 2, that is either ON or OFF.
- Figure below shows two HMMs S^1 and S^2 generated by two different data streams, the aggregate energy consumption can be modelled using PoHMMs as shown below.



- Each data stream is used to train the model until the objective function reaches the threshold value.
- Models are trained from the randomly sampled data streams, the parameters thus learned are provided to the randomly sampled test set to obtain the probability distribution of the gaussians given the data.
- The probability distributions obtained from individual data stream is compared with the probability distribution obtained from the total metered data using KL Divergence.

Results

Performance comparison between REDD, FH and Enernoc datasets is shown below.



Background Study

TREC CDS Task

Problem: To retrieve the full biomedical articles that are relevant for answering generic clinical questions ("test", "diagnosis", "treatment") about medical records.

- Documents : A total of 7,33,138 full text biomedical articles are available from the PubMed Central[4]. Each article is represented by a unique number (PMCID) with the nxml extension.

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- Judgements: Participants were asked to submit the results in trec_eval format, a maximum of 5 runs each consisting of 1000 ranked list of PMCID per topic.

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Approach

- The approach used by [2] was to extract key phrases from the topic using syntactic analysis and wikipedia articles such that rarely and most commonly used key phrases were removed. They then expandded these medical key phrases according to several mediacal knowledge bases like UMLS. Finally performed retrieval using Lucene and LDA based retrieval systems.
- In another approach, the author experimented and evaluated variety of retrieval models (Indri, Lucene, Xapian) and indexing strategies as well as ways of combining different models and indexes. They used Medical Subject Headings (MeSH) to keep only the important concepts. They concluded that Lucene with vector space model and Xapian using BM25 had similar results and that there ensemble can lead for better results.

Further Reading

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Thanks