

Automatic Metadata Extraction

The High Energy Physics Use Case

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August 26, 2015

Motivation

- ▶ INSPIRE-HEP digital library at CERN contains over 1 Million documents
- ▶ Manual curation of high energy physics (HEP) papers may be automated with machine learning techniques
- ▶ Custom datasets and specialised features required to model HEP paper characteristics

Aims

Take existing state-of-the-art system for metadata extraction to:

- ▶ demonstrate a qualitative difference between HEP and general papers;
- ▶ propose improvements to model features;
- ▶ run experiments to confirm these improvements, and;
- ▶ draw conclusions about what characterises good feature engineering.

Outline

Introduction

Automatic Metadata Extraction

Data and Features

Key Results

Conclusions

Metadata Extraction

- ▶ *Metadata* refers to content useful to the bibliographic identification of the document
- ▶ *Extraction* refers to the classification of metadata within the document text
- ▶ Several automatic approaches exist: stylistic analysis, knowledge-base, machine learning (CRFs, HMMs, SVMs) ...

Metadata Extraction (Illustration)

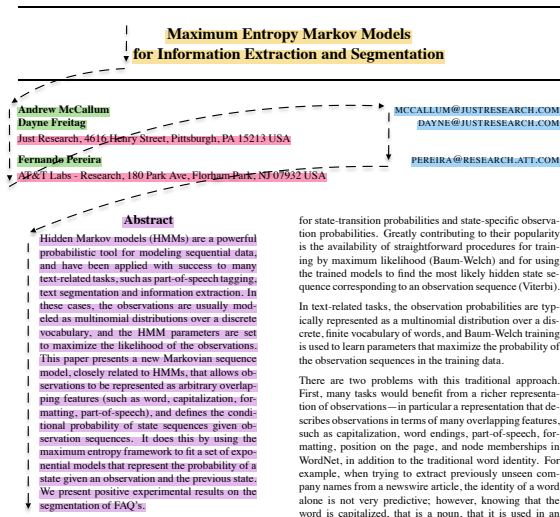


Figure: Tagging of a document header section.

Why Conditional Random Fields?

- ▶ Transition interdependencies implies graphical structure best modelled as a structured sequence
- ▶ Modelling conditional distribution, $p(\mathbf{y}|\mathbf{x})$, sufficient for classification
- ▶ Exploit rich information about observations, \mathbf{x} , without explicitly modelling the underlying probability distribution
- ▶ Classifying metadata may greatly benefit from modelling rich text features (punctuation, font size, layout ...)

GROBID

- ▶ Selected according to performance in study comparing AME systems [2]
- ▶ Open source Java-based tool developed at INRIA, France
- ▶ Manages *cascade* of CRF models for annotating papers in progressively finer detail
- ▶ Uses C++ library *Wapiti* for back-end calculations (model training, prediction)

GROBID - CRF Cascade

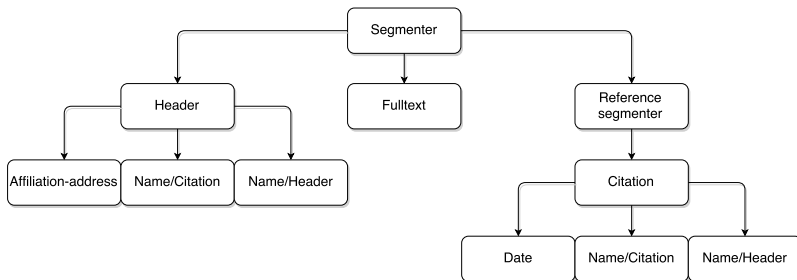


Figure: Cascade of models used by Grobid

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Identification of beauty and charm quark jets at LHCb

The LHCb collaboration[†]

Abstract

Identification of jets originating from beauty and charm quarks is important for measuring Standard Model processes and for searching for new physics. The performance of algorithms developed to select b - and c -quark jets is measured using data recorded by LHCb from proton-proton collisions at $\sqrt{s} = 7$ TeV in 2011 and at $\sqrt{s} = 8$ TeV in 2012. The efficiency for identifying a $b(c)$ jet is about 65%(25%) with a probability for misidentifying a light-parton jet of 0.3% for jets with transverse momentum $p_T > 20$ GeV and pseudorapidity $2.2 < \eta < 4.2$. The dependence of the performance on the p_T and η of the jet is also measured.

Submitted to JINST

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Figure: Collaboration field in header section.

HEP Paper Characteristics (ii)

LHCb collaboration

R. Aaij³⁸, B. Adeva³⁷, M. Adinolfi⁴⁶, A. Affolder⁵², Z. Ajaltouni⁵, S. Akar⁶, J. Albrecht⁹, F. Alessio³⁸, M. Alexander⁵¹, S. Ali⁴¹, G. Alkhazov³⁰, P. Alvarez Cartelle⁵³, A.A. Alves Jr⁵⁷, S. Amato², S. Amerio²², Y. Amhis⁷, L. An³, L. Anderlini^{17,g}, J. Anderson⁴⁰, M. Andreotti^{16,f}, J.E. Andrews⁵⁸, R.B. Appleby⁵⁴, O. Aquines Gutierrez¹⁰, F. Archilli³⁸, P. d'Argent¹¹, A. Artamonov³⁵, M. Artuso⁵⁹, E. Aslanides⁶, G. Auremma^{25,n}, M. Baalouch⁵, S. Bachmann¹¹, J.J. Back⁴⁸, A. Badalov³⁶, C. Baesso⁶⁰, W. Baldini^{16,38}, R.J. Barlow⁵⁴, C. Barschel³⁸, S. Barsuk⁷, W. Barter³⁸, V. Batozskaya²⁸, V. Battista³⁹, A. Bay³⁹, L. Beaucourt⁴, J. Beddow⁵¹, F. Bedeschi²³, I. Bediaga¹, L.J. Bel⁴¹, I. Belyaev³¹, E. Ben-Haim⁸, G. Bencivenni¹⁸, S. Benson³⁸, J. Benton⁴⁶, A. Berezhnoy³², R. Bernet⁴⁰, A. Bertolin²², M.-O. Bettler³⁸, M. van Beuzekom⁴¹, A. Bien¹¹, S. Bifani⁴⁵, T. Bird⁵⁴, A. Birnkraut⁹, A. Bizzeti^{17,i}, T. Blake⁴⁸, F. Blanc³⁹, J. Blouw¹⁰, S. Blusk⁵⁹, V. Bocci²⁵, A. Bondar³⁴, N. Bondar^{30,38}, W. Bonivento¹⁵, S. Borghi⁵⁴, M. Borsato⁷, T.J.V. Bowcock⁵², E. Bowen⁴⁰, C. Bozzi¹⁶, S. Braun¹¹, D. Brett⁵⁴, M. Britsch¹⁰, T. Britton⁵⁹, J. Brodzicka⁵⁴, N.H. Brook⁴⁶, A. Bursche⁴⁰, J. Buytaert³⁸, S. Cadeddu¹⁵, R. Calabrese^{16,f}, M. Calvi^{20,k}, M. Calvo Gomez^{36,p}, P. Campana¹⁸, D. Campora Perez³⁸, L. Capriotti⁵⁴, A. Carbone^{14,d}, G. Carboni^{24,l}, R. Cardinale^{19,j}, A. Cardini¹⁵, P. Carniti²⁰, L. Carson⁵⁰, K. Carvalho Akiba^{2,38}, R. Casanova Mohr³⁶, G. Casse⁵², L. Cassina^{20,k}, L. Castillo Garcia³⁸, M. Cattaneo³⁸, Ch. Cauet⁹, G. Cavallero¹⁹, R. Cenci^{23,l}, M. Charles⁸, Ph. Charpentier³⁸, M. Chefdeville⁴, S. Chen⁵⁴, S.-F. Cheung⁵⁵, N. Chiapolini⁴⁰, M. Chrzaszcz⁴⁰, X. Cid Vidal³⁸, G. Ciezarek⁴¹, P.E.L. Clarke⁵⁰, M. Clemencic³⁸, H.V. Cliff⁴⁷, J. Closier³⁸, V. Coco³⁸, J. Cogan⁶, E. Cogneras⁵, V. Cogoni^{15,e}, L. Cojocariu²⁹, G. Collazuol²², P. Collins³⁸, A. Comerma-Montells¹¹, A. Contu^{15,38}, A. Cook⁴⁶, M. Coombes⁴⁶, S. Coquereau⁸, G. Corti³⁸, M. Corvo^{16,f}, I. Counts⁵⁶, B. Couturier³⁸, G.A. Cowan⁵⁰, D.C. Craik⁴⁸, A. Crocombe⁴⁸, M. Cruz Torres⁶⁰, S. Cunliffe⁵³, R. Currie⁵³, C. D'Ambrosio³⁸, J. Dalseno⁴⁶, P.N.Y. David⁴¹, A. Davis⁵⁷, K. De Bruyn⁴¹, S. De Capua⁵⁴, M. De Cian¹¹, J.M. De Miranda¹, L. De Paula²,

Figure: Collaboration author list.

HEP Paper Characteristics (iii)

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Figure: Collaboration affiliation list.

HEP Paper Characteristics (iv)

encode different attribute dimensions of an input data space. A good glyph design can enable users to conduct visual search more efficiently during interactive visualization, and facilitate effective learning, memorizing and using the visual encoding scheme. A less effective visual design may suffer from various shortcomings such as being perceptually confusing, semantically ambiguous, difficult to learn and remember, or unable to accommodate low-resolution display devices.

-
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Manuscript received 31 March 2012; accepted 1 August 2012; posted online 14 October 2012; mailed on 5 October 2012.

For information on obtaining reprints of this article, please send e-mail to: tvcg@computer.org.

Figure: Discontinuous header data.

Training Data

Two models addressed:

- ▶ *header* model, which classifies *word* tokens as <title>, <author>, <abstract>, etc.
- ▶ *segmentation* model, which classifies *line* tokens as <header>, <body>, <references>, etc.
- ▶ Custom HEP training sets collected for each
- ▶ Customs sets combined with existing CORA datasets during experimentation

Model	HEP	CORA
Header	157 papers	2506 papers
Segmentation	169 papers	125 papers

Table: Number of training instances for each model from each dataset.

Feature Engineering

- ▶ Experiments run for different features designed to enhance the models *header* and *segmentation*
- ▶ 66 experiments run testing combinations of features, model and CV configuration.

Method	Model
Baseline	both
Block Size	header
Character Classes	segmentation
Dictionaries	header
Levenshtein Distance	segmentation
Regularisation	header
Token Extensions	segmentation

Table: Feature engineering experiments

Dictionary Features (*header*)

Dictionaries were derived from the INSPIRE-HEP corpus:

- ▶ affiliations
- ▶ authors
- ▶ collaborations
- ▶ journals
- ▶ titles
- ▶ stop words*

Dictionary-based features were then modelled as,

$$f_{\text{dict}_i}(x_t) = \mathbb{1}_{\{x_t \in \text{dict}_i\}},$$

for each dictionary, dict_i .

Character Class Features (*segmentation*)

Feature functions defined to be,

$$f_{\text{class}_i}(x_t) = \frac{1}{|x_t|} \sum_{n=1}^{|x_t|} \mathbb{1}_{\{x_{ti} \in \text{class}_i\}},$$

for each character class, class_i , where x_t is a token (line), and x_{ti} is the i th character in the line.

Class	Regex
Spacing	$r'[\backslash s]'$
Lower case	$r'[a-z]'$
Upper case	$r'[A-Z]'$
Numeric	$r'[\backslash d]'$
Punctuation	$r'[.,?;:]'$
Special character	$r'^{[\backslash sa-zA-Z d.,?;:]}'$

Table: Character classes used as features.

Levenshtein Distance Features (*segmentation*)

Define similarity function,

$$\text{similarity}(a, b) = 1 - \frac{\text{lev}_{a,b}(|a|, |b|)}{\max(|a|, |b|)}.$$

Then feature function,

$$f_{lev}(x_t) = \begin{cases} 0 & \text{if } 0 \leq \text{similarity}(x_t, x_{t-1}) \leq T_1 \\ 1 & \text{if } T_1 \leq \text{similarity}(x_t, x_{t-1}) \leq T_2 \\ \vdots & \vdots \\ N-1 & \text{if } T_{N-1} \leq \text{similarity}(x_t, x_{t-1}) \leq 1 \end{cases}$$

where T_1, T_2, \dots, T_{N-1} are thresholds selected to create the N categories.

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Header Model (Best Features)

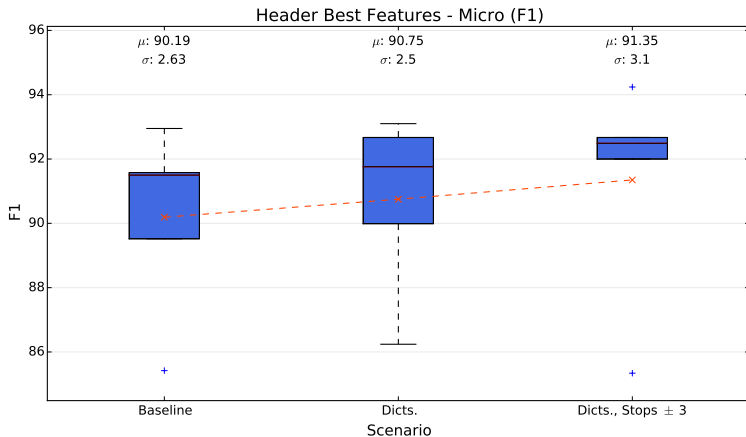


Figure: Best features for header model.

Segmentation Model (Header Field)

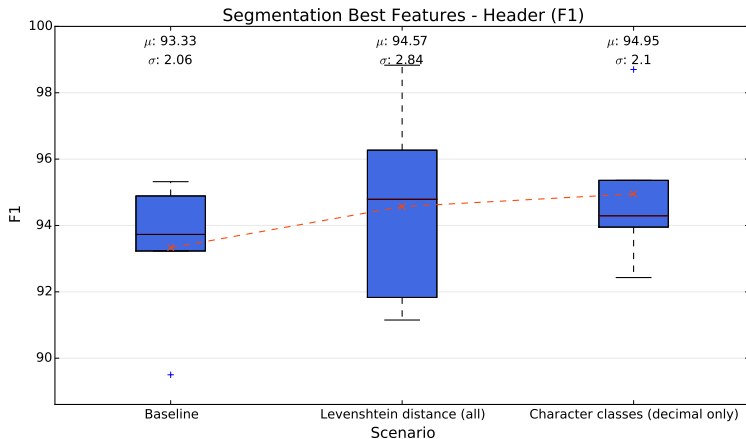


Figure: Best features for segmentation model <header> field.

Segmentation Model (References Field)

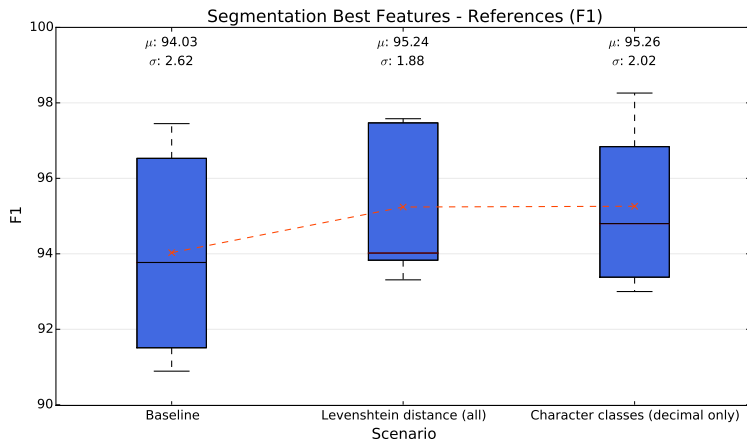


Figure: Best features for segmentation model <references> field.

Segmentation Model (Baseline Confusion Matrix)

Confusion matrix - Segmentation (Baseline, HEP)

acknowledgement	544	5	258			10	1		
annex	13	1805	9078			67	1	3	46
body	142	2601	185466		162	303	45	41	590
cover				259	5	26	1		
footnote	6	8	495		1171	47	42	31	18
header		3	906	43	32	12211	11	6	36
headnote		18	372		56	76	1380	52	35
page	2	10	136		18	12	17	2257	12
references	115		392		11	124	18	5	10871
	acknowledgement	annex	body	cover	footnote	header	headnote	page	references

Figure: Baseline confusion matrix for segmentation model.

Segmentation Model (Character Class Confusion Matrix)

Confusion matrix - Segmentation (Character Classes, HEP)

acknowledgement	616		185			17			
annex	16	1573	9293			3	3	1	124
body	51	2555	185735		87	530	52	28	312
cover				259	5	24	3		
footnote		19	472		1205	39	58	8	17
header			311	1	41	12863	8	3	21
headnote		6	354		55	59	1428	57	30
page		5	116		5	10	22	2297	9
references			433		14	96	21	6	10966
	acknowledgement	annex	body	cover	footnote	header	headnote	page	references

Figure: Confusion matrix for segmentation model with character classes.

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Conclusions

- ▶ Qualitative difference between HEP and general papers demonstrated (through inspection, subsampling).
- ▶ Valuable new datasets produced.
- ▶ Successful features offered a dimensionality reduction: dictionaries (12% error reduction), character classes (24% and 21% on <header> and <references> classifications).



R. Aaij, B. Adeva, M. Adinolfi, A. Affolder, Z. Ajaltouni, S. Akar, J. Albrecht, F. Alessio, M. Alexander, S. Ali, et al. Identification of beauty and charm quark jets at LHCb. *arXiv preprint arXiv:1504.07670*, 2015.



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