Automatic Metadata Extraction
The High Energy Physics Use Case

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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

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 ...)

Mathematical Formulation

A CRF factorises in the following as,

$$\mathrm{p}(\mathbf{y}|\mathbf{x}) = \frac{\mathrm{p}(\mathbf{x},\mathbf{y})}{\sum_{y'} \mathrm{p}(\mathbf{x},\mathbf{y}')} = \frac{1}{Z(\mathbf{x})} \exp\left\{ \sum_k \lambda_k F_k(y_t, y_{t-1}, x_t) \right\},$$

- $Z(\mathbf{x}) = \sum_{y'} \exp\left\{ \sum_k \lambda_{ij} F_k(y'_t, y'_{t-1}, x_t) \right\}$, known as the parition function.
- $F_k(\mathbf{x}, y) = \sum_t^T f_k(\mathbf{x}, y)$, where f_k is a function expressing a feature.
- It is in choosing the form of the functions, $f(\cdot)$, explicitly that we perform feature engineering.

Solution Approach

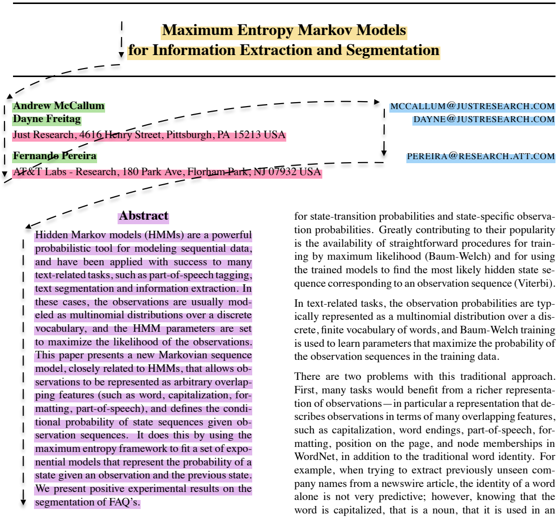
- Formuluate convex function, maximum log likelihood estimator, $l(\Lambda)$, where $\Lambda = \{\lambda_k\}_{k=1}^{K}$.
- Train (determine Λ) with gradient ascent technique, L-BFGS. Each iteration, I, requires forward-backward algorithm to compute $Z(\mathbf{x^{(n)}})$ for each of N samples – $\mathcal{O}(INT|S|^2)$.
- Prediction with Viterbi algorithm – $\mathcal{O}(T|S|^2)$.

Outline

Metadata Extraction

- *Metadata* refers to content useful to the bibliographpic 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)



Maximum Entropy Markov Models for Information Extraction and Segmentation

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Abstract

Hidden Markov models (HMMs) are a powerful probabilistic tool for modeling sequential data, and have been applied with success to many text-related tasks, such as part-of-speech tagging, text segmentation and information extraction. In these cases, the observations are usually modeled as multinomial distributions over a discrete vocabulary, and the HMM parameters are set to maximize the likelihood of the observations. This paper presents a new Markovian sequence model, closely related to HMMs, that allows observations to be represented as arbitrary overlapping features (such as word, capitalization, formatting, part-of-speech), and defines the conditional probability of state sequences given observation sequences. It does this by using the maximum entropy framework to fit a set of exponential models that represent the probability of a state given an observation and the previous state. We present positive experimental results on the segmentation of FAQ's.

for state-transition probabilities and state-specific observation probabilities. Greatly contributing to their popularity is the availability of straightforward procedures for training by maximum likelihood (Baum-Welch) and for using the trained models to find the most likely hidden state sequence corresponding to an observation sequence (Viterbi).

In text-related tasks, the observation probabilities are typically represented as a multinomial distribution over a discrete, finite vocabulary of words, and Baum-Welch training is used to learn parameters that maximize the probability of the observation sequences in the training data.

There are two problems with this traditional approach. First, many tasks would benefit from a richer representation of observations—in particular a representation that describes observations in terms of many overlapping features, such as capitalization, word endings, part-of-speech, formatting, position on the page, and node memberships in WordNet, in addition to the traditional word identity. For example, when trying to extract previously unseen company names from a newswire article, the identity of a word alone is not very predictive; however, knowing that the word is capitalized, that is a noun, that it is used in an

Figure: Tagging of a document header section.

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

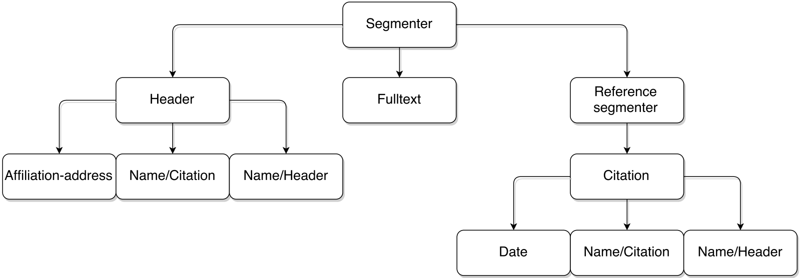

Figure: Cascade of models used by Grobid

Outline

HEP Paper Characteristics (i)

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 $\sqrt{s} = 7\,\text{TeV}$ in 2011 and at $\sqrt{s} = 8\,\text{TeV}$ 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 $p_{\mathrm{T}} > 20\,\text{GeV}$ 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)

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.

HEP Paper Characteristics (iii)

LHCb collaboration

R. Aaij[38], B. Adeva[37], M. Adinolfi[46], A. Affolder[52], Z. Ajaltouni[5], S. Akar[6], J. Albrecht[9], F. Alessio[38], M. Alexander[51], S. Ali[41], G. Alkhazov[30], P. Alvarez Cartelle[53], A.A. Alves Jr[57], S. Amato[2], S. Amerio[22], Y. Amhis[7], L. An[3], L. Anderlini[17,g], J. Anderson[40], M. Andreotti[16,f], J.E. Andrews[58], R.B. Appleby[54], O. Aquines Gutierrez[10], F. Archilli[38], P. d'Argent[11], A. Artamonov[35], M. Artuso[59], E. Aslanides[6], G. Auriemma[25,n], M. Baalouch[5], S. Bachmann[11], J.J. Back[48], A. Badalov[36], C. Baesso[60], W. Baldini[16,38], R.J. Barlow[54], C. Barschel[38], S. Barsuk[7], W. Barter[38], V. Batozskaya[28], V. Battista[39], A. Bay[39], L. Beaucourt[4], J. Beddow[51], F. Bedeschi[23], I. Bediaga[1], L.J. Bel[41], I. Belyaev[31], E. Ben-Haim[8], G. Bencivenni[18], S. Benson[38], J. Benton[46], A. Berezhnoy[32], R. Bernet[40], A. Bertolin[22], M.-O. Bettler[38], M. van Beuzekom[41], A. Bien[11], S. Bifani[45], T. Bird[54], A. Birnkraut[9], A. Bizzeti[17,i], T. Blake[48], F. Blanc[39], J. Blouw[10], S. Blusk[59], V. Bocci[25], A. Bondar[34], N. Bondar[30,38], W. Bonivento[15], S. Borghi[54], M. Borsato[7], T.J.V. Bowcock[52], E. Bowen[40], C. Bozzi[16], S. Braun[11], D. Brett[54], M. Britsch[10], T. Britton[59], J. Brodzicka[54], N.H. Brook[46], A. Bursche[40], J. Buytaert[38], S. Cadeddu[15], R. Calabrese[16,f], M. Calvi[20,k], M. Calvo Gomez[36,p], P. Campana[18], D. Campora Perez[38], L. Capriotti[54], A. Carbone[14,d], G. Carboni[24,l], R. Cardinale[19,j], A. Cardini[15], P. Carniti[20], L. Carson[50], K. Carvalho Akiba[2,38], R. Casanova Mohr[36], G. Casse[52], L. Cassina[20,k], L. Castillo Garcia[38], M. Cattaneo[38], Ch. Cauet[9], G. Cavallero[19], R. Cenci[23,t], M. Charles[8], Ph. Charpentier[38], M. Chefdeville[4], S. Chen[54], S.-F. Cheung[55], N. Chiapolini[40], M. Chrzaszcz[40], X. Cid Vidal[38], G. Ciezarek[41], P.E.L. Clarke[50], M. Clemencic[38], H.V. Cliff[47], J. Closier[38], V. Coco[38], J. Cogan[6], E. Cogneras[5], V. Cogoni[15,e], L. Cojocariu[29], G. Collazuol[22], P. Collins[38], A. Comerma-Montells[11], A. Contu[15,38], A. Cook[46], M. Coombes[46], S. Coquereau[8], G. Corti[38], M. Corvo[16,f], I. Counts[56], B. Couturier[38], G.A. Cowan[50], D.C. Craik[48], A. Crocombe[48], M. Cruz Torres[60], S. Cunliffe[53], R. Currie[53], C. D'Ambrosio[38], J. Dalseno[46], P.N.Y. David[41], A. Davis[57], K. De Bruyn[41], S. De Capua[54], M. De Cian[11], J.M. De Miranda[1], L. De Paula[2],

Figure: Collaboration author list.

HEP Paper Characteristics (iv)

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[44] *Institute for Nuclear Research of the National Academy of Sciences (KINR), Kyiv, Ukraine*

Figure: Collaboration affiliation list.

Training Data

- Two models addressed: *header* and *segmentation*
- 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*

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,

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

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

Class	Regex
Spacing	r‘[\s]’
Lower case	r‘[a-z]’
Upper case	r‘[A-Z]’
Numeric	r‘[\d]’
Punctuation	r‘[.,?:;]’
Special character	r‘[^\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,

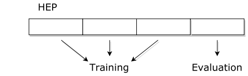
$$f_{lev}(x_t) = \begin{cases} 0 & \text{if } 0 \leq \text{similarity}(x_t, x_{t-1}) \leq T_1 \\ 1 & \text{if } T_1 \leq \text{similarity}(x_t, x_{t-1}) \leq T_2 \\ \vdots & \quad\vdots \\ \text{N-1} & \text{if } T_{N-1} \leq \text{similarity}(x_t, x_{t-1}) \leq 1 \end{cases}$$

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

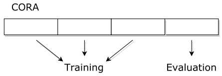
Outline

Experiment Setup

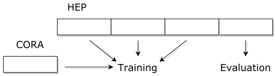
- 66 experiments run testing combinations of features, model and CV configuration.
- Models judged primarily on micro average F_1 score, but also with reference to key classes where necessary.



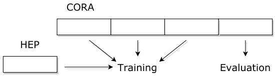
(a) CV HEP



(b) CV CORA



(c) CV HEP append CORA



(d) CV CORA append HEP

Figure: Cross-validation configurations used in experiments.

Header Model (Subsampling CORA dataset)

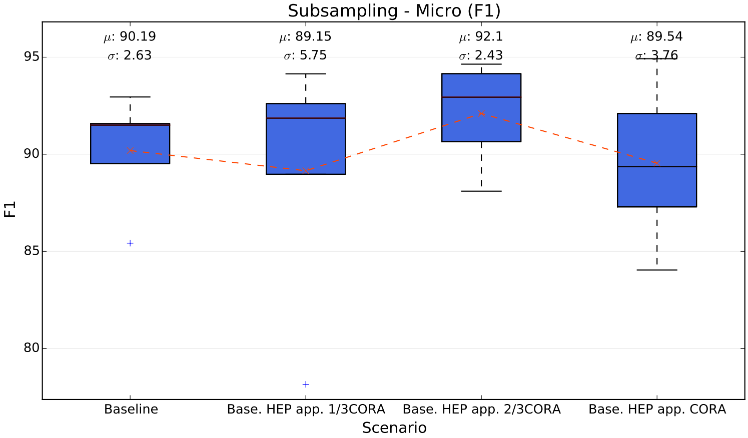


Figure: Appending subsamples of CORA dataset in baseline evaluation.

Header Model (Best Features)

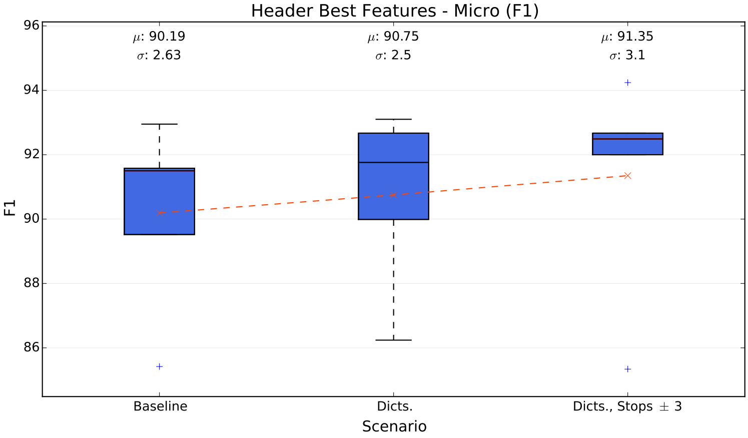


Figure: Best features for header model.

Segmentation Model (Best Features)

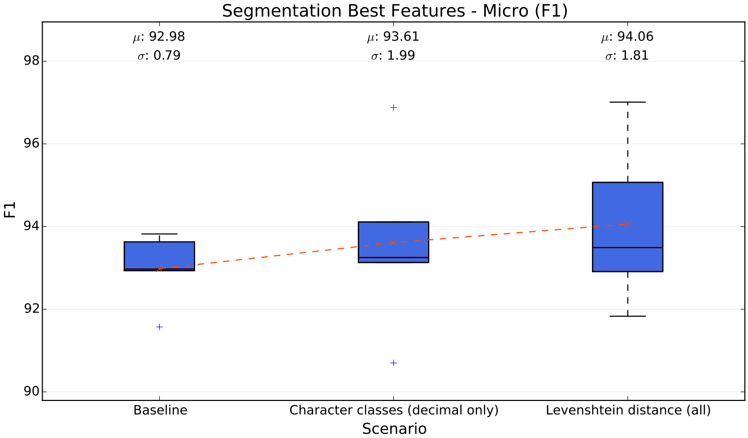


Figure: Best features for segmentation model.

Segmentation Model (Header Field)

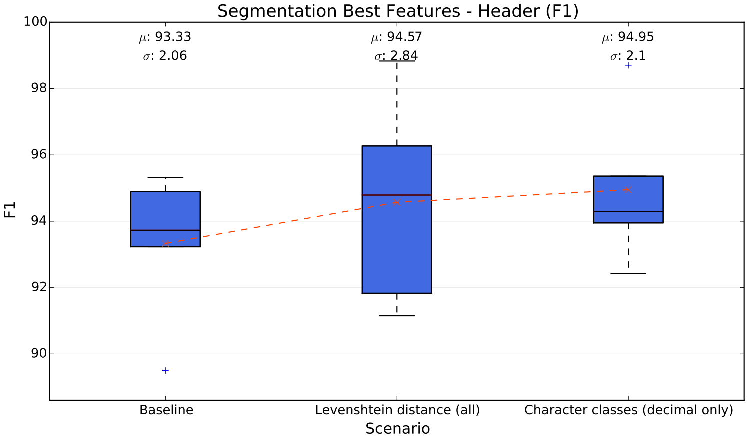


Figure: Best features for segmentation model <header> field.

Segmentation Model (References Field)

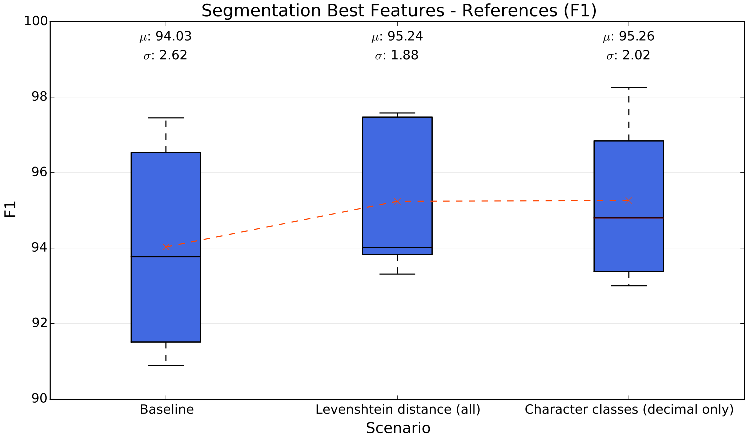


Figure: Best features for segmentation model <references> field.

Segmentation Model (Baseline Confusion Matrix)

Confusion matrix - Segmentation (Baseline, HEP)

	acknowledgement	annex	body	cover	footnote	header	headnote	page	references
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

Figure: Baseline confusion matrix for segmentation model.

Segmentation Model (Character Class Confusion Matrix)

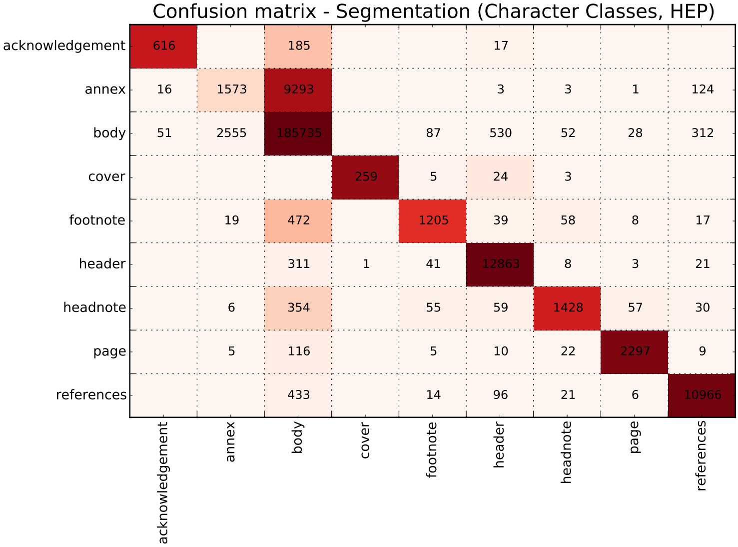


Figure: Confusion matrix for segmentation model with character classes.

Outline

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.
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