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 CRFs?

- 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

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

where $Z(\mathbf{x}) = \sum_{y'} \exp\left\{ \sum_k \lambda_{ij} F_k(y'_t, y'_{t-1}, x_t) \right\}$ is known as the partition function, ensuring probabilities sum to 1.

$F_k(\mathbf{x}, y) = \sum_t^T f_k(\mathbf{x}, y)$, where f_k is a (typically boolean) function describing one of several features about a token.

The form of the functions themselves, $f(\cdot)$, are known in Wapiti (Section **??**) as *templates*. It is in choosing these explicitly that we perform feature engineering.

Solution Approach

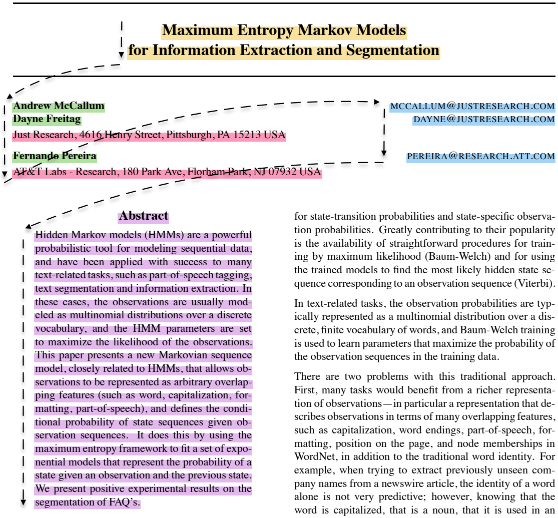
- Formuluate convex maximum log likelihood estimator, $l(\Lambda)$, where $\Lambda = \{\lambda_k\}_{k=1}^{K}$
- Train (determine Λ) with gradient ascent technique, L-BFGS. Each iteration, I, requires forward-backward algorithm to compute $Z(\mathbf{x^{(n)}})$ for each of N samples – $\mathcal{O}(INT|S|^2)$.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

Outline

Metadata Extraction

- *Metadata* refers to content useful to the identification of the document
- *Extraction* refers to the identification of metadata within the document text
- Several automatic approaches exist: stylistic analysis, knowledge-base, machine learning, ...

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 (training, prediction)

GROBID - CRF Cascade

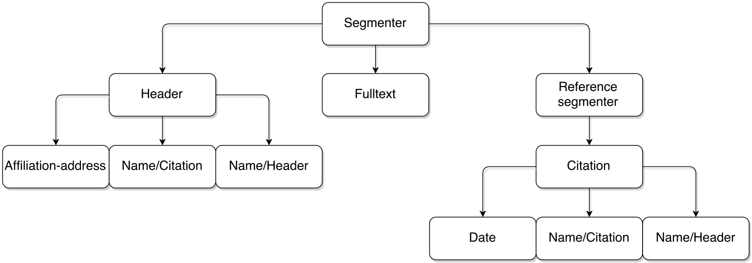
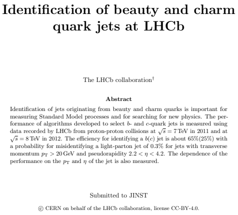


Figure: Cascade of models used by Grobid

Outline

HEP Paper Characteristics



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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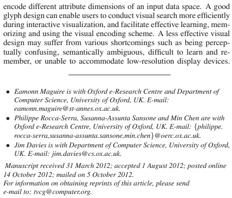
(a) Collaboration field in header section.



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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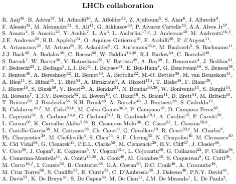
Manuscript received 31 March 2012; accepted 1 August 2012; posted online 14 October 2012; mailed on 5 October 2012.
For information on obtaining reprints of this article, please send e-mail to: tvcg@computer.org.

(b) Discontinuous header data.



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],

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Figure: Figure (A) shows a collaboration field in a header section. Figure

Training Data

Two models addressed: *header* and *segmentation*

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

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

Dictionary Features

Dictionaries for INSPIRE-HEP affilations, authors, collaborations, journals, and titles. Stop words modelled as additional dictionary.

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

Character Class Features

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

for each character class, class_i, where x_t is a token (hence a line for the *segmentation* model), and x_{ti} is the *ith* character in the line. For the decimal (round down) case, we then define,

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, along with the regular expressions used to count them.

Levenshtein Distance Features

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

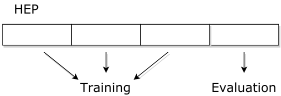
Due to the constraints on numeric features (see Section **??**), we must discretise the result. Thus, for a given line, x_t, we define the feature function,

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

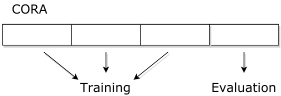
where T_1, T_2, ..., T_{N-1} are thresholds selected to create the N categories. We try several thresholding strategies in our experimentation (see Section **??**).

Outline

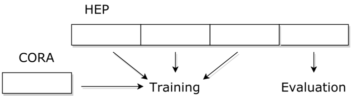
Experiment Setup



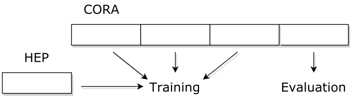
(a) CV HEP



(b) CV CORA



(c) CV HEP append CORA



(d) CV CORA append HEP

Figure: The different cross-validation configurations used in our experiments. Figures (A) and (B) show cross-validation on HEP and CORA sets independently. Figures (C) and (D) show cross-validation on the HEP and CORA datasets respectively, appending the other at training time.

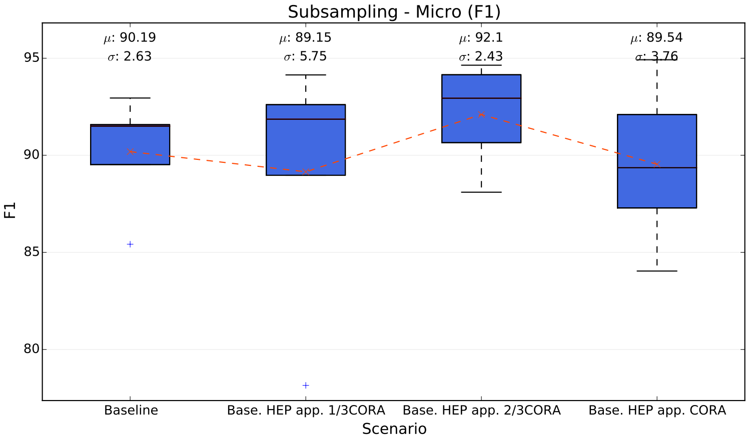


Figure: Baseline confusion segmentation

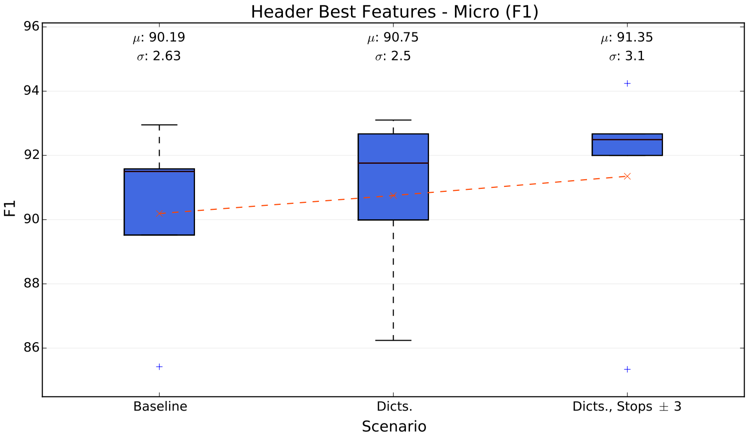


Figure: Baseline confusion segmentation

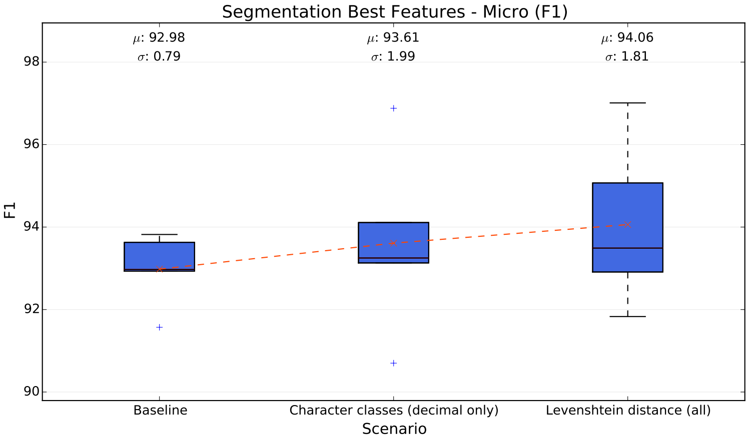
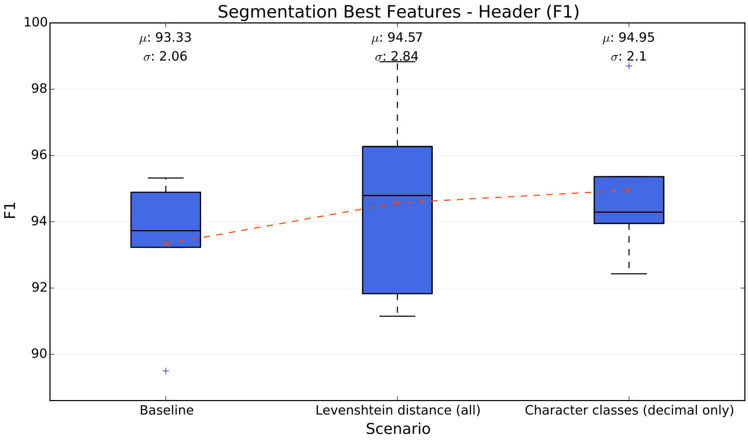


Figure: Baseline confusion segmentation



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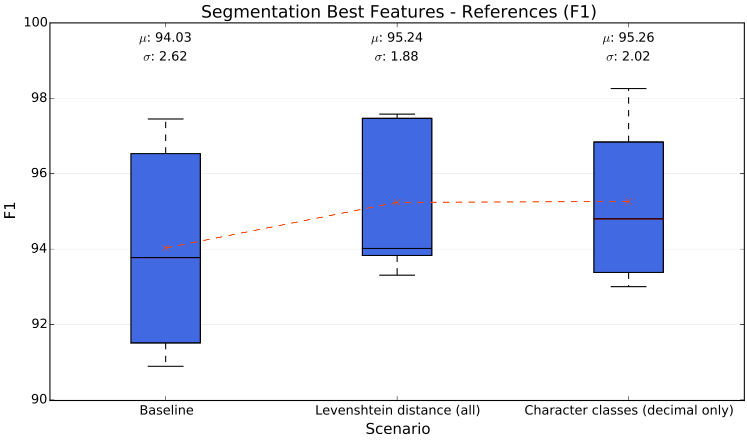

Figure: Baseline confusion segmentation

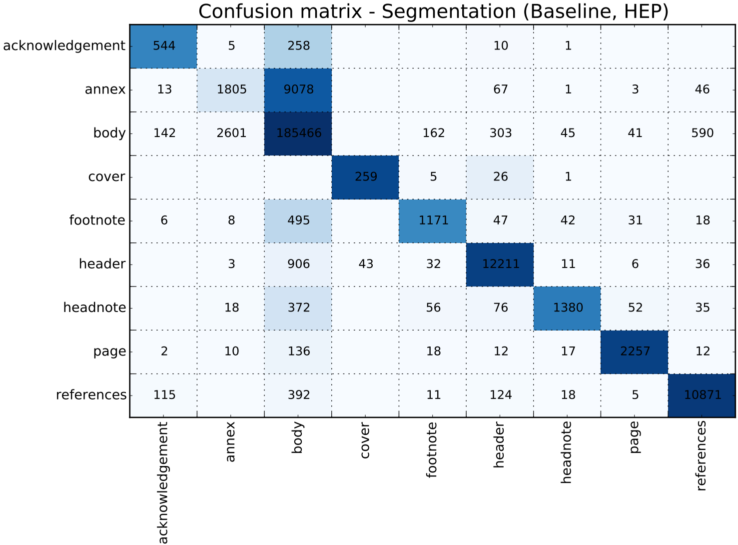

Figure: Classes confusion segmentation

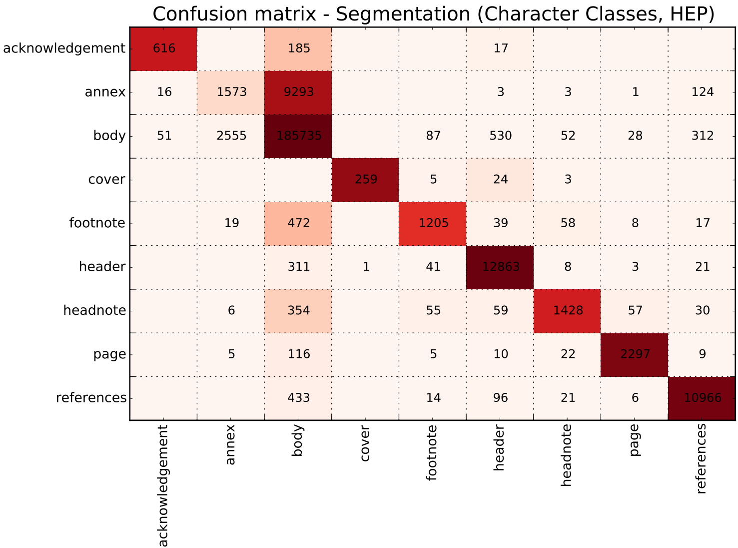

Figure: Classes confusion segmentation

Outline

Conclusions

- Qualitative difference between HEP and general papers demonstrated (through inspection, subsampling)
- Most successful features were those offering a dimensionality reduction: dictionaries (12% error reduction), character classes (24% and 21% on header and reference 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.

M. Lipinski, K. Yao, C. Breitinger, J. Beel, and B. Gipp.
Evaluation of header metadata extraction approaches and tools for scientific pdf documents.
In *Proceedings of the 13th ACM/IEEE-CS joint conference on Digital libraries*, pages 385–386. ACM, 2013.

E. Maguire, P. Rocca-Serra, S.-A. Sansone, J. Davies, and M. Chen.
Taxonomy-based glyph design–with a case study on visualizing workflows of biological experiments.
Visualization and Computer Graphics, IEEE Transactions on, 18(12):2603–2612, 2012.