What's in a name?

Nigel Collier Associate Professor National Institute of Informatics 2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo 101-8430

www.research.nii.ac.jp/~collier collier@nii.ac.jp

Outline

- Introduction
 - An overview of the text mining task
- The nature of biological entities
 - The state of the art
 - Challenges
- Training computers to do bio-NE
 - Knowledge acquisition
 - Methodology
 - Results from JNLPBA
- Discussion and future work

Introduction

Activate_in(JAK1,non-human T lymphocytes)

Activate(JAK1,STAT1)

"Finally, in other cell types the correlation between JAK1 activation and the induction of STAT1 has suggested that this protein may activate STAT1 in non-human T lymphocytes."

Ontology		Instances		
Taxonomy	Axioms	Concepts	Coreference	Relations

```
Activate(JAK1,STAT1),
Activate_in(JAK1,non-human T lymphocytes)
```



The Pipeline Architecture



Tasks in semantic indexing

NE task definition: given a document (full article or abstract), identify nonoverlapping sequences of word tokens and assign them an entity class representing the concepts of interest.



Why is NER necessary?

• New terms are being invented all the time

"We have previously identified a J binding protein (JBP1) involved in propagating J synthesis. We have now identified a homolog of JBP1, JBP2, containing a domain related to the SWI2/SNF2 family of chromatin remodeling proteins that is upregulated in bloodstream form cells and interacts with nuclean chromatin" [DiPaolo, C., Kieft, R., Cross, M. and Sabatini, R. Mol. Cell 17(3) 2005]



 Biological databases are not up to date and do not list all variant forms

The nature of biological entities

The JNLPBA 2004 shared task

- Systematic evaluation of entity tagging by machines against a human gold standard
- Domain was 'human' 'blood cell' 'transcription factor'
- Open system task entrants were free to use whatever resources they could think of in addition to the GENIA corpus (~2000 human annotated abstracts);
- Common evaluation of machine capability on a human annotated gold standard (~400 newly annotated MEDLINE abstracts)



Kim, J.D., Ohta, T., Tsuruoka, Y., Tateisi, Y. and Collier, N. (2004), "Introduction to the Bio-Entity Recognition Task at JNLPBA", in proceedings of the Joint Workshop on Natural Language Processing in Biomedicine and its Applications, 28-29 August, Geneva, Switzerland.

Example from the JNLPBA shared-task

A complete inhibition of DNA synthesis by dexamethasone (Dx) could be observed when IL 2-depleted cultures of CTL were either incubated for 6 h with the hormone prior to the addition of IL 2 or treated simultaneously with Dx and a low concentration of IL 2.



- The task takes a particular view of the ontology which is suitable for tagging non-overlapping spans of text.
- Nevertheless compromises need to be made at both the schema level and in the annotation guidelines.
 - e.g. "dexamethasone" is ignored
 - e.g. "IL 2" is not tagged as a protein inside "IL 2-depleted cultures"





Test collection characteristics

- 20,546 sentences, 472,006 tokens
- Named entity counts: 30,269 protein (15.1%), 9533 DNA (4.8%), 951
 RNA (0.5%), 6718 cell type (3.4%), 3830 cell line (1.9%)



Evaluation Metrics

- Precision and Recall
 - Precision: Correct answer/Answers produced
 - Recall: Correct answers/Total possible correct answers
- F-measure
 - Where β is a parameter representing relative importance of P and R

$$F = \frac{(\beta^2 + 1)PR}{(\beta^2 P + R)}$$

Experience in shared-evaluations

- The state-of-the-art in news entity tagging is at 'near human' levels of performance – high 90s F-score (e.g. MUC 1995, CoNLL 2003);
- The state of the art for bio-entity tagging in JNLPBA shared evaluation task is in the mid-70s

Challenges in biological entity recognition [1]

- Term variant forms
 - Orthographic variants (e.g. T cell, t cell | Interleukin-2, Interleukin 2)
 - Use of capitalization and hyphenation is idiosyncratic
 - Morphological variants (e.g. protein, proteins | anti-CD28, CD28)
 - Aliases and abbreviations (e.g. human immunodeficiency type 2, HIV-2)
- Descriptive naming
 - e.g. normal thymic epithelial cells [Zhou et al. 2003]
- Uncontrolled naming
 - Experience in BioCreative 1b tagging of gene names in model organisms confirmed that fly genes were far more difficult than yeast or mouse.

Challenges in biological entity recognition [2]

- Name length
 - e.g. 47 kDa sterol regulatory element binding factor
 18.6% of NEs in GENIA v3.0 have >= length 4 [Zhou et al. 2003]
 - Average gene name is 2.09 in BioCreative 1a compared to 1.69 for organization names in MUC-6
- Syntactic variants
 - Conjunction and disjunction (e.g. c- and v-rel (proto) oncogenes)
 - 2.1% of NEs in GENIA v3.0
- Semantic ambiguity
 - Due to context (e.g. interleukin-2 as PROTEIN or DNA)
 - Due to granularity (e.g. interleukin-2 gene expression as OTHER_NAME)

Challenges in biological entity recognition [3]

- Widespread use of abbreviation
 - e.g. APC as activated protein c, aphidicholin, atrial premature complexes, adenomatous polyposis coli, antigen presenting cells [Tsuruoka et al. 2003]
 - Challenging cases, e.g. GNAT as Gcn5-related Nacetyltransferase [Schwartz & Hearst 2003]

Training computers to do bio-NE





Knowledge markup with OOF





Kawazoe, A., Kitamoto, A. and Collier, N. (2004), in proceedings LREC'2004, Lisbon, Portugal.

Major features of OOF

- Handles large document collections using internal archiving of documents with MySQL database
- Simple process of ontology creation
 - Support for taxonomies, classes, properties, individuals and annotations
- Annotation of text/image with linkage to ontologies
- Annotation of pooled coreference relations using referred individuals
- Three formats for ontology/annotation export
 - RDF(S)
 - In-line XML
 - HTML
- Version 2 release from December (<u>http://research.nii.ac.jp/~collier</u>) – end of advertising!

Feature types

Knowledge type	Feature name			
Surface text	Word features			
Orthographic	Othographic features			
Morphological	Prefix/suffix			
	Part of speech (POS)			
	Lemma			
Syntactic	Parenthesis matching			
	Head of noun phrase			
	Predicate-argument relations			
Semantic	Previous NE tags			
Discourse	Abbreviation full forms			

Examples of features

- 1. Activation activation Activation - N NOM_SG A231 ic O
- 2. of of activation mod PREP O100 lw O
- 3. JAK jak kinases kinase attr N NOM_SG J200 03 B-PROTEIN
- 4. kinases kinase kinases of pcomp N NOM_PL K522 04 I-PROTEIN
- 5. and and - CC A530 lw O
- 6. STAT stat proteins protein attr ABBR NOM_SG S330 03 B-PROTEIN
- 7. proteins protein proteins - N NOM_PL P635 04 I-PROTEIN
- 8. by by protein mod PREP B000 lw O
- 9. interleukin-2 interleukin-2 alpha interferon attr N NOM_SG I536 11 B-PROTEIN
- 10. and alpha interferon attr CC A530 lw O
- 11. interferon interferon alpha alpha attr N NOM_SG I536 lw B-PROTEIN
- 12. alpha alpha by pcomp N NOM_SG A410 01 I-PROTEIN
- 13., , - - cm O
- 14.but but - CC B300 lw O
- 15.not not - NEG-PART N300 lw O
- 16.the the - DET T000 lw O
- 17.T t receptor cell attr ABBR NOM_SG T000 06 B-PROTEIN
- 18.cell cell receptor antigen attr N NOM_SG C400 05 I-PROTEIN
- 19.antigen antigen receptor receptor attr N NOM_SG A532 lw I-PROTEIN 20.receptor receptor receptor - - N NOM_SG R213 04 I-PROTEIN
- 21., , - - cm O

SVM Model

- Based on work of Vapnik 1995
- Most popular model used in JNLPBA 5 out of 8 systems (others were HMM, MEMM, CRF)
- Non-probabilistic classifier
 - Maximum margin hyperplane
 - Use of kernel functions to perform non-linear classification with minimal computational cost
- Robust to noise can ignore outliers
- Multi-classifiers are built up from binary classifiers
- Achieved state-of-the-art performance in many classification tasks

Classification in SVMs



Input Space

Feature Space

SVM Features

Word	Activati on	of	JAK	kinases	and	STAT	proteins	by
POS	Ν	PREP	Ν	N	CC	ABBR	N	PREP
Orthogr aphy	ic	lvv	uc	Iw	lvv	uc	lw	lw
Class	0	0	B- PROTEIN	I- PROTEIN	0	B- PROTEIN	B- PROTEIN	0



40 60 80

% of data used for training

Surface word, orthograph lemma, head noun, abbre full forms

Named entity experiments on Bio1 Named entity experiments on Bio1 Named entity results on Bio1 75 E-score - Surface word and POS F-score Surface word only Surface word and POS - Surface word and lemm 45 60 80 40 60 80 100 20 60 80 % of data set used for training % of data set used for training % of data set used for training Named entity experiments on Bio1 Named entity experiments on Bio1 Named entity experiments on Bio1 - Surface word or Surface word and PO Surface word only Surface word and POS -ecore -score Curlops word and land Surface word and orthogra emma, head nour Surface word, orthography lemma, head noun Surface word, orthography lemma, head noun, NP 60 80 60 80 60 80 % data used in training % data used in training % of data used for training Named entity experiments on Bio1 Named entity experiments on Bio1 Named entity experiments on Bio1 Surface word onl Surface word and POS and POS Surface word, ortho emma, head noun urface word, orthograph Surface word, orthograph lemma, head noun, NP Surface word, orthograph Surface word, orthograph emma, head noun, p Surface word, orthograp 40 60 80 % of data set used for training 60 80

Feature farming

2 data sets x 10 way split of the data set x 10 fold cross validation x 9 feature splits = 1800experiments in about 24 hours

lemma, head noun, abl

% of data set used for training

Results [1]: Surface words



- Intuition
 - We've seen:
 - [JAK kinase]
 protein
 - and
 - [Jun]_{protein}
 - Guess that:
 - [Jun kinase]_{protein}

Results [2]: Words plus POS



- Intuition
 - We've seen:
 - [JAK_N kinase_N]
 protein
 - Hypothesize that:
 - [?_N kinase_N]
 protein

Results [3]: Words and lemma



- Intuition
 - We've seen:
 - [JAK_JAK kinases_kinase]_{protein}
 - Hypothesize that:
 - [JAK_JAK kinase_kinase]_{protein}

Results [4]: Words and orthography



- Intuition
 - We've seen:
 - [LMP_cap -_hyp
 1_dig]_{protein}
 - Hypothesize that:
 - [AP_cap -_hyp 2_dig]_{protein}

Results [5]; Words, orthography, lemma and head noun



- Intuition
 - We've seen:
 - [T_cell cells_cell]
 cell type
 - Hypothesize that:
 - [breast_cell carcinoma_cell cells_cell]_{cell type}

Results [6]: Words, orthography, lemma, head noun, noun phrase



Results [7]: Words, othography, lemma, head noun, parentheses


Results [8]: Words, orthography, lemma, head noun, abbreviations



Results [9]: Words, orthography, lemma, head noun, bio-suffixes/prefixes



Influence of data set size on models

• Results for selected models on JNLPBA



Influence of data set size on classes

• Results for the best model on JNLPBA



Confusion matrix for JNLPBA

#	Value	1	2	3	4	5	6	7	8	9	10	11	error
1	0	77.9	0.8	0.2	0.4	0.1	0.2	0.0	0.0	0.0	0.0	0.0	2.7
2	B-protein	1.3	3.3	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	1.6
3	I-protein	1.5	0.3	2.8	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	2.0
4	B-cell type	0.4	0.01	0.0	1.2	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.6
5	I-cell type	0.6	0.0	0.1	0.2	2.1	0.0	0.0	0.0	0.1	0.0	0.0	1.0
6	B-DNA	0.3	0.2	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.0	0.0	0.5
7	I-DNA	0.6	0.1	0.2	0.0	0.0	0.0	0.9	0.0	0.0	0.0	0.0	0.9
8	B-cell line	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.3
9	I-cell line	0.3	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.4	0.0	0.0	0.6
10	B-RNA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.1
11	I-RNA	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1
	error	5.4	1.5	1.3	0.6	0.7	0.3	0.4	0.1	0.2	0.0	0.1	10.5

Analysing PAS frames in biology: PASBio

- Extend Propbank [Kingsbury and Palmer, 2002]
- Collect a corpus of domain texts
- Identify the major verbs (predicates) that indicate events
- Extract example sentences
- Analyse verb senses and argument roles with domain experts
- See if this fits with PropBank's existing frames
- If not then add a new frame and annotate selected sentences
- Perform machine learning to automate annotation

Predicate Argument Structure Frame - Microsoft Internet Explorer Ele Ede time Favores Tools task	
🔾 Back • 💭 - 🖹 🗟 🐔 🔑 Search 👷 Favorites 🤣 🝰 🐁 🚽 📖 🛐 🖋 😫	
ldów 🍓 http://research.ni.ac.go/~coller/projects/PASBio/block.htm	💌 🔛 Go 🖘 🔭 🊒
Predicate <i>block</i>	•
Roleset block.01 (WordNet Sense 3)	
Roles:	
Ar g0 causer agent Ar g1. theme (process or entity being stopped)	
Examples:	
$\frac{MEDLINE Na.1}{Mataions at the 3' splice size that specifically block step II do not affect the association of hPrys 16 and 17 with the splitstage of stray I prior to recognize of the 3' splice size.$	cessome, indicating that these factors may function at a
Arg0: Monatoons at the F splice and Arg1: step II	
EMBO No.1	
Tagetin is more specific for distinguishing between different RNA polymerases because it blocks RNA polymerase durin action is independent of different animhon factors.	ag elongation (Mathews and Durbin, 1994), i.e. its
Arg0. ±	
Argl: RNA polymerase during elongation	
EMBO No.2	
A downsteam kinase appears to be ersenial for agrin-mediated signaling, since staarooporme blocks agrin-induced AC MuSK phosphorylation (Wallace, 1994, Fubrer et al., 1997)	3.R clustering and phorphorylation without inhibiting
Arg9: staurosporine Arg1: agmi-induced AChR chuttering and phosphorylation	
EMBO No.3	
	€ (-3-2s)

http://research.nii.ac.jp/~collier/projects /PASBio/index.html



Wattarujeekrit, T., Shah, P. and Collier, N. (2004), "PASBio: predicate-argument structures for event extraction in molecular biology", in BMC Bioinformatics, 5:155.



Using predicate argument information to constrain types





Wattarujeekrit, T. and Collier, N. (2005), in proceedings of the Eighth International Conference on Discovery Science, Singapore.

Scores for selected predicates on JNLPBA

Predicate	Lexical model	Lexical model + dependency path + voice + head pair + trans/intrans	Improvement
Encode	56.6	57.6	+1.0
Recognize	47.2	49.4	+2.2
Block	51.2	52.0	+0.8
Lead	57.0	57.5	+0.5

Discussion and future work

Developments in JNLPBA

- State-of-the-art systems have taken the feature sets into new areas:
 - Use of character n-grams for affix features
 - Use of gazetteers (derived from LocusLink, GO etc.)
 - Use of syntactic information
 - Use of external resources (BNC, Google search)
 - Context holding mechansims (previously predicted entities)

System	Features	F-score
Zho	af,or,gn,gz,po,tr,a b,ca	72.6
Fin	lx,af,sh,gz,po,sy,a b,do,pa	70.1
Set	lx,af,or,sh,gz,tr	69.8
Son	af,or,po,np	66.3
Zha	lx	64.8
Rös	af,or,gn,ln	64.0
Par	Af,or,sh,gn,wv,po ,np,tr	63.0
Lee	Af,po	49.1

Final thought [1]

- State of the art still seems far away from human performance
 - Maybe 80 F-score is good enough for practical applications? Must be led by biologists needs.
- But what *is* human performance?
 - About 97% for MUC-7 on news data
 - We have some evidence, e.g. 87% (Hirschman, 2003), 89% (Demetrious and Gaizauskas, 2003)
 - ... but not really enough people are too busy doing NE to consider the task itself!
 - Need inter-annotator agreement scores and <u>intra-annotator</u> agreement scores

Final thought [2]

- But what is the 'right' level of knowledge?
- A study of IAA or NE should also consider what levels of knowledge the annotators use to make their decisions:
 - Sentential
 - Document
 - World knowledge
 - Guess

Final thought [3]

- What kinds of ontologies are appropriate for annotation of text spans?
- BioCreative (2004) 1b normalization of gene names showed one good way
 - Mapping entities to some conceptual definition in an ontology
 - Combines named entity with coreference resolution on real world ontologies
 - But seems to add a level of complexity
- As a community we need to decide on a consensus for the way forward – traditional MUC-style NER or ontology class mapping or a combination of both

Conclusion

- Biomedical NER has been successful
 - A step forward into defining semantics in domain texts
 - Resources were created and re-used, models adapted, tools deployed – but not nearly enough deployment yet
 - Started us on the track to disciplined methodologies and open evaluations
 - Insights into the nature of terminology in the domain
- Not far enough yet?
 - 80 F-score seems to be the upper limit, but why? Is 80 Fscore enough? Is it the task definition, the data or the knowledge-level?
- Cross domain comparisons
 - No formal way yet to compare difficulties across domains (e.g. news vs biology, EMBOJ vs Nature, different subsets of MEDLINE)

Acknowledgements

- Terminology annotation
 - Koichi TAKEUCHI (Okayama U.)
- Coreference annotation
 - Ai KAWAZOE (NII)
 - Asanobu KITAMOTO (NII)
- Predicate-argument annotation
 - Tuangthong
 WATTARUJEEKRIT (NII)
 - Parantu SHAH (EMBL)
- Rhetorical structure
 annotation
 - Yoko MIZUTA (NII)
 - Anthony MULLEN (Tsuda, U.)

- Verb semantics
 - Anna KORHONEN (Cambridge U.)
- Bio-domain knowledge
 - Shoko KAWAMOTO (NAIST, NII)
 - Asao FUJIYAMA (NII, RIKEN)
- JNLPBA 2004 shared task
 - Jin-Dong KIM (U. Tokyo)
 - Tomoko OHTA (U. Tokyo)
 - Yoshimasa TSURUOKA (U. Tokyo)
 - Yuka TATEISHI (U. Tokyo)
- Funding
 - NII, JSPS

Recent Publications [1]

- Collier, N., Nazarenko, A., Baud, R. and Ruch, P. (2005) "Recent advances in natural language processing for biomedical applications", in vol. 74, no. 11, International Journal of Medical Informatics, Elsevier (in press).
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- Yacov Kogan, Nigel Collier, Serguei Pakhomov and Michael Krauthammer (2005), "Towards Semantic Role Labeling & IE in the Medical Literature", in proceedings of <u>the American Medical Informatics Association annual symposium</u>, Washington DC, USA, October 22-26 (in press).
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Recent Publications [2]

- Kim, J.D., Ohta, T., Tsuruoka, Y., Tateisi, Y. and Collier, N. (2004), "Introduction to the Bio-Entity Recognition Task at JNLPBA", in proceedings of the Joint Workshop on Natural Language Processing in Biomedicine and its Applications, 28-29 August, Geneva, Switzerland.
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Recent Publications [3]

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