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Two hierarchical text categorization approaches for BioASQ semantic indexing challenge

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BioASQ challenge 2013

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2. Description of our systems
   - HACE framework
   - Rebayct

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   - Adaptations
   - Preprocessing
   - Tested configurations

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Motivation

- Joint work of CoLe group (Univ. of Vigo) and UTAI group (Univ. of Granada)
- Previous independent work on related small/medium size problems
  - Legal documents: { parliamentary initiatives (UTAI); public grants and subsidies (CoLe) }
  - Medium size thesauri (EUROVOC + custom thesaurus)
  - Both dealing with Spanish texts (also Galician for CoLe)
  - Minimal linguistic processing (no tagging, no lemmatization, no NER)
- Thesarus topic assigment as a hierarchical text categorization problem
  - Top-down scheme using a local classifier per node approach (CoLe)
  - Bayesian network induced from thesaurus hierarchy (UTAI)

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Objectives

1. Test the scalability of our proposals with large real-world data
   - BioASQ Task 1A: *Large-Scale Online Biomedical Semantic Indexing*
   - Large hierarchy of descriptors and large training set $\rightarrow$ size and time restrictions
2. Evaluate the suitability of a pure text categorization approach for semantic indexing with MeSH $\rightarrow$ minimal linguistic processing
   - Very different domain $\rightarrow$ complex terminology

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Origins of our systems

HACE framework

Text categorization on a public grants/subsidies collection

- Small size custom thesaurus ($\approx$ 1800 descriptors)
- Medium/large size documents
- A few labeling inconsistence in training documents
- Additional requirement: return ”many” results (search for a high recall)
  - Human curators will postprocess system output

Rebayct

Text categorization on a parliamentary initiatives collection

- EUROVOC thesaurus ($\approx$ 4000 descriptors)
- Very small size documents (1-2 paragraphs)
- Additional requirement: return ”many” results (search for a high recall)
  - Human curators will postprocess system output

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HACE framework (I)

Generic framework for hierarchical categorization *(under development)*

Top-down *Local Classifier per Node Approach*

- Local binary classifier trained for each node in the hierarchy
- Is current node (or its descendants) pertinent as label?
- Pachinko-like top-down traversal of local classifiers

Able to deal with tree and DAG structured taxonomies

Plug-in architecture with several components for:

- selecting sets of positive examples with a bottom-up procedure
- selecting sets of negative examples
- feature selection at each local model (IG, Chi squared, ...)
- classification algorithm to perform the ”routing” decisions at each local model
- dealing with unbalanced classes (weighting, boundary negative examples, split negative example set in an ensemble of classifiers)

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HACE framework (II)

Specific features for large scale hierarchical text categorization

- Textual features computation backed by a Lucene index
- Bottom-up positive example selection (from positive examples sets in descendant nodes)
  - avoid unmanageable training sets on top levels
  - random selection among descendant positive examples
  - k-means clustering based selection $\rightarrow$ selecting examples close to centroids
- Guided top-down search using a simplified k-nearest neighbours
  - query the Lucene index to get a set of promising labels from most similar documents
  - top-down search starts at grandparents nodes $\rightarrow$ avoids premature discard of useful paths

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HACE framework (III)

Contextual routing decisions (not tested in BioASQ data)

- **Objective:** try to reduce false negatives (mainly in top levels)
- Two classifier per node model { content based / context based
- Exploiting bottom-up information (*metafeatures*) coming from content based routing decisions performed by descendant nodes (and optionally by ancestor and sibling nodes)
- Roughly inspired by *classifier chain* approaches in multilabel classification
  - Adds to content based features a set of *metafeatures* about decisions of surrounding models
- Moderate performance improvements + high training/classification cost

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Rebayct (I)

Builds a Bayesian network using:

1. thesaurus hierarchical structure
2. terms (tokens) taken from { descriptor labels / non-descriptor labels }
3. terms (tokens) taken from training documents

Elements

- Concept nodes (representing thesaurus concepts/nodes)
- Descriptor and Non-Descriptor nodes (representing descriptor and non descriptor labels)
- Term nodes (representing words [tokens])

Every concept node C linked with three virtual nodes

- H_C: info. from BT (*Broader Term*) relationships in the thesaurus
- E_C: info. from descriptor and non-descriptor labels (synonymy)
- T_C: info. from training documents

Efficient OR-gate model to define conditional probabilities.

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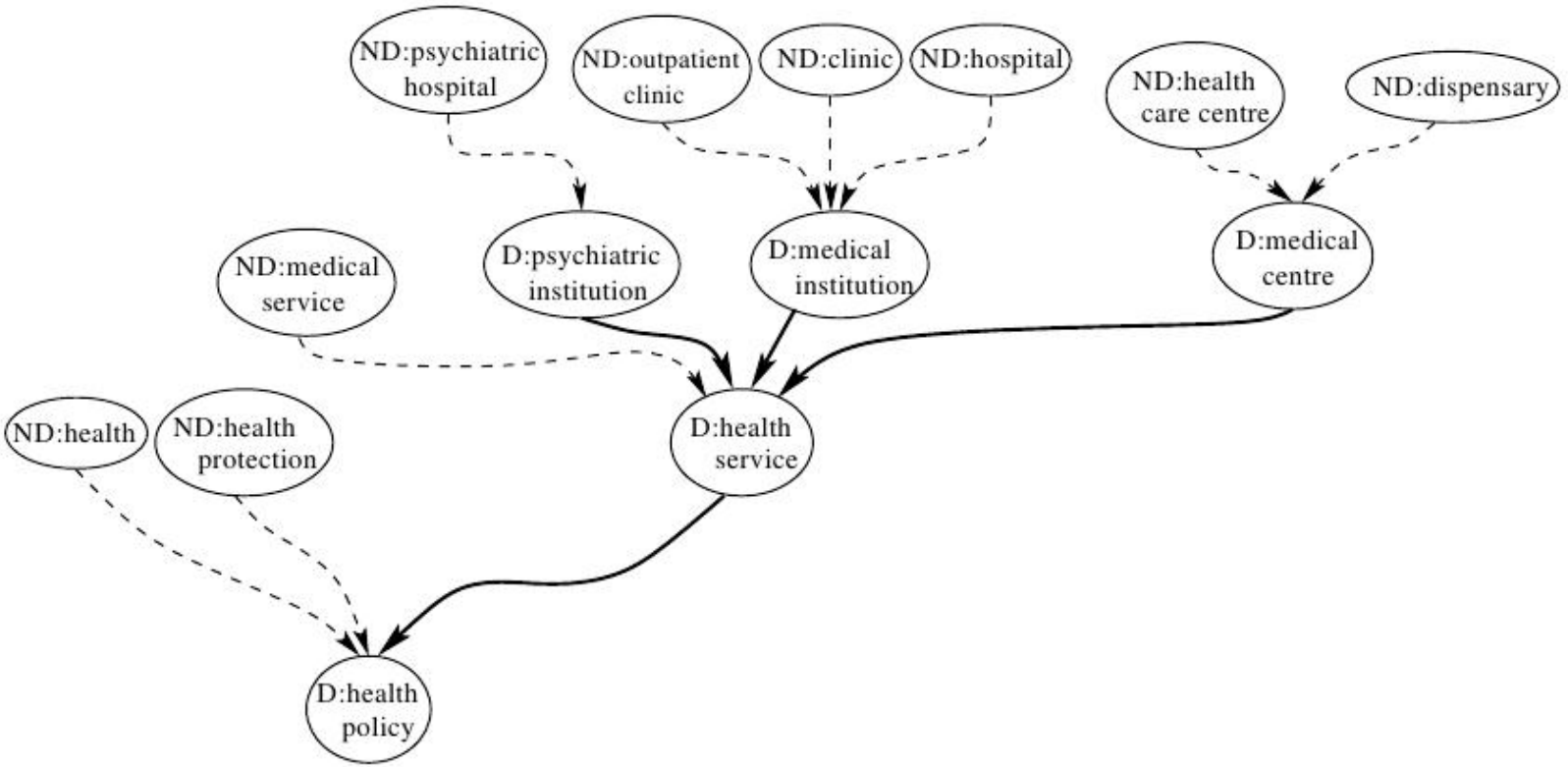
Rebayct (II)

Thesaurus fragment (D: descriptors, ND: non-descriptors)



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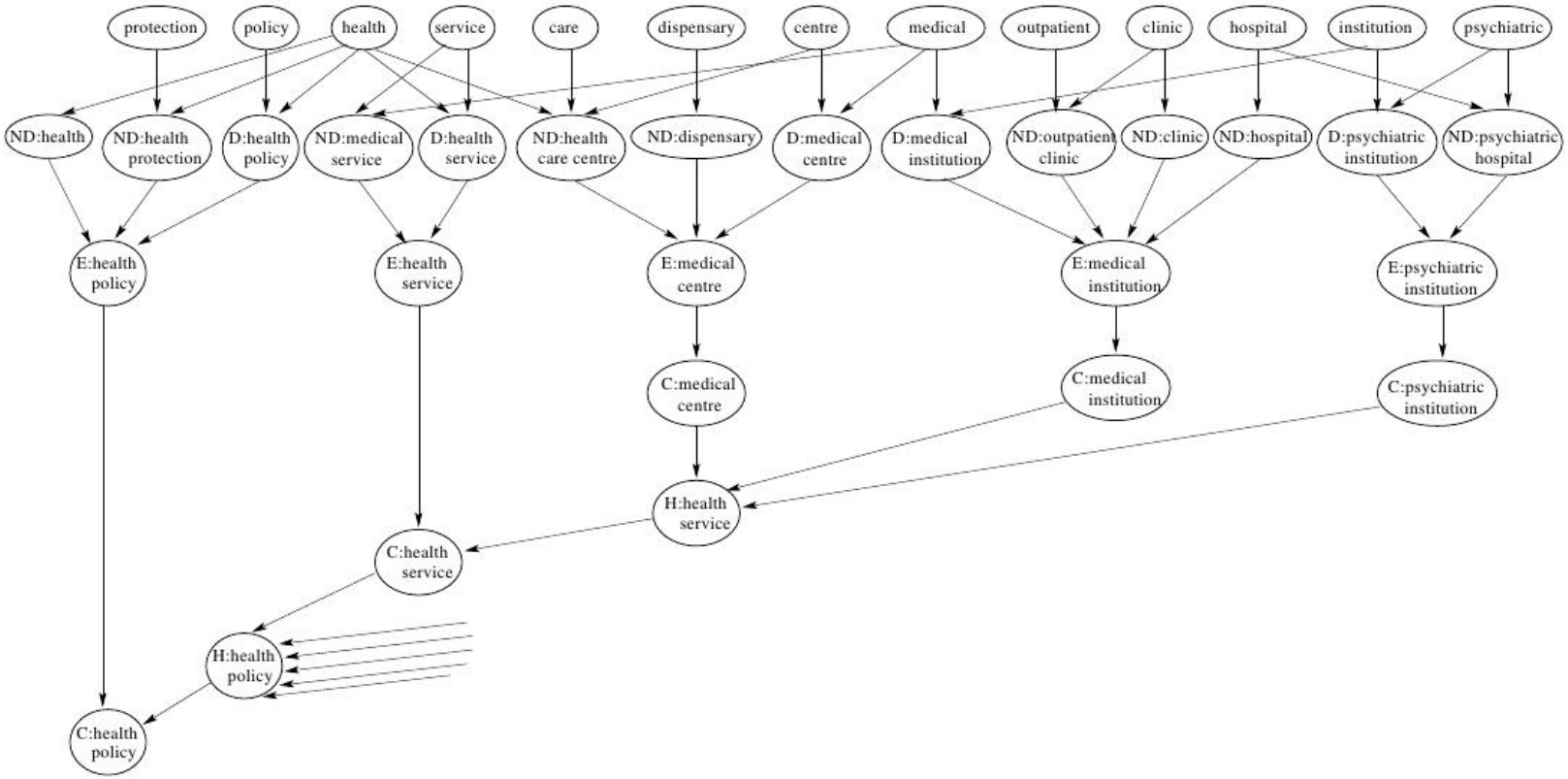
Rebayct (II)

Bayesian network build from thesaurus hierarchy and descriptor and non-descriptor equivalence relationships



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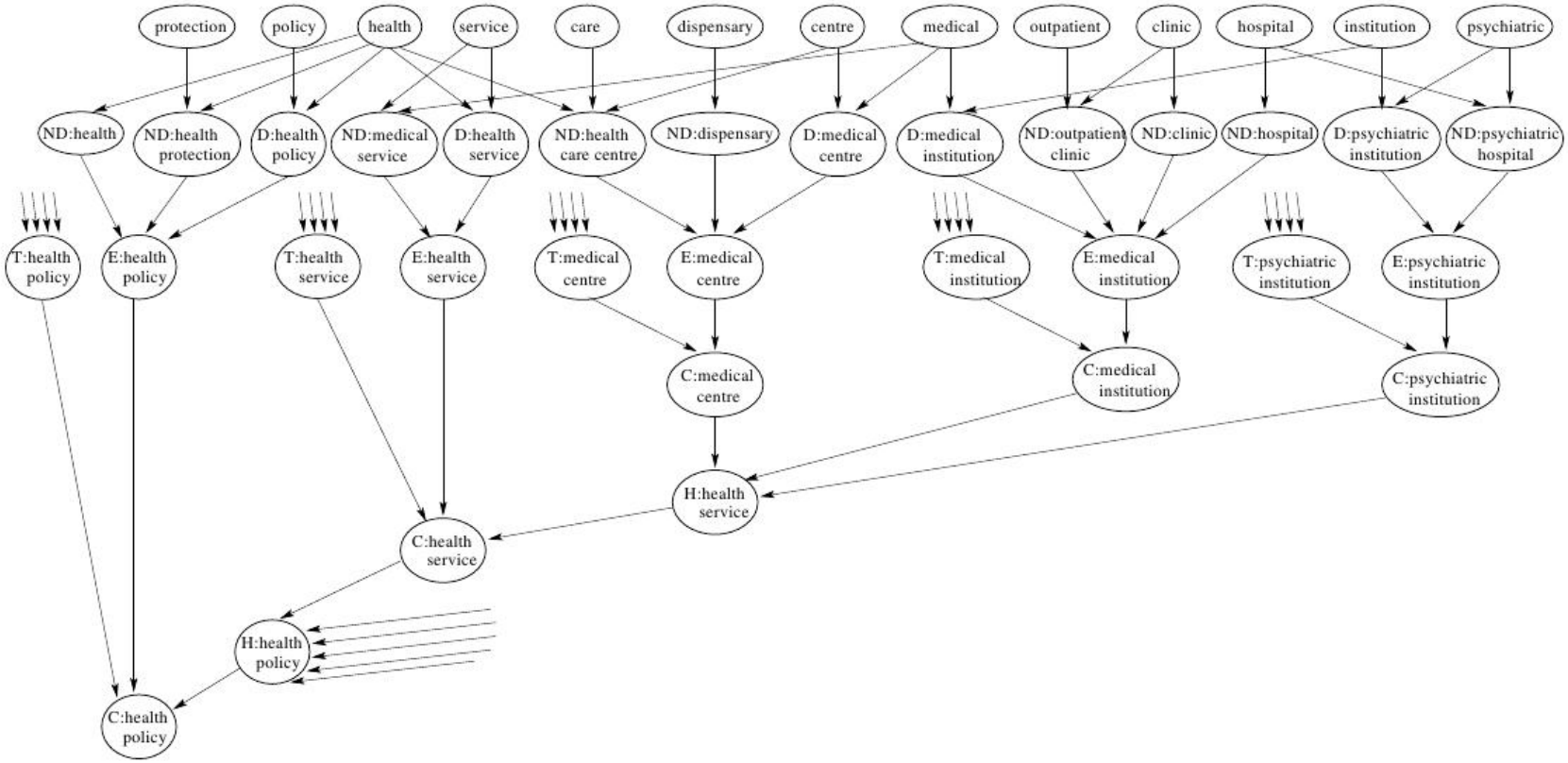
Rebayct (II)

Bayesian network after adding terms from training documents



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Adaptations for BioASQ challenge

Own concept taxonomy with a DAG structure extracted from 2013 XML version of MeSH

- Hierarchical relationships created from *TreeNumber* elements
- *TreeNumbers* describe the places a MeSH descriptor occupies inside the 16 concept taxonomies

Results

- DAG with 26,702 nodes (excludes 151 descriptors from subhierarchy V)
- 36,647 parent-child relationship with only two cycles
  - descriptors D009014 (*Morals*) + D004989 (*Ethics*)
  - descriptors D006885 (*Hydroxybutyrates*) + D020155 (*3-Hydroxybutyric Acid*)
- 108,117 related terms (synonyms or lexical variants) [non-descriptors for Rebayct]

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Problem: spurious relationships in the final DAG taxonomy

Example: *eye* as { part of *face* / a *sense organ* } leads to consider *eyebrows* as an element of a *sense organ*

```
Body Regions;A01
  ...
  Head;A01.456
    Ear;A01.456.313
    Face;A01.456.505
      Cheek;A01.456.505.173
      Chin;A01.456.505.259
      Eye;A01.456.505.420
        Eyebrows;A01.456.505.420.338
        Eyelids;A01.456.505.420.504
          Eyelashes;A01.456.505.420.504.421
      Forehead;A01.456.505.580
      Mouth;A01.456.505.631
        Lip;A01.456.505.631.515
      Nasolabial Fold;A01.456.505.682
      Nose;A01.456.505.733
      Parotid Region;A01.456.505.750
    Scalp;A01.456.810
    ...
```

```
Sense Organs;A09
  Ear;A09.246
    (44 descendants)
  Eye;A09.371
    Anterior Eye Segment;A09.371.060
      (20 descendants)
    Anterior Capsule of the Lens;A09.371.061
    Axial Length, Eye;A09.371.199
    Eyelids;A09.371.337
      Conjunctiva;A09.371.337.168
      Eyelashes;A09.371.337.338
      Meibomian Glands;A09.371.337.614
    Lacrimal Apparatus;A09.371.463
    ...
    Retina;A09.371.729
      (21 descendants)
    Sclera;A09.371.784
      Tenon Capsule;A09.371.839
    Uvea;A09.371.894
      (6 descendants)
  Nose;A09.531
  ...
```

No disambiguation info. on training data to avoid it

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Preprocessing for BioASQ challenge

Only elementary text processing on train and validation documents.

- stop-word removal using a standard English stop-word list
- default English stemmer from the Snowball project

Also: alternative collection extracting word bigrams from descriptor labels and document text after stop-word removal

- simple way to capture some complex terms (but far from perfect)

Rebayct scalability limitations

- Extract a reduced training set of 1,242,670 documents (10 %)
- $\approx$ 50 more representative documents for every descriptor taken from Lucene index
- Split into 5 groups (248.534 training instances) to train

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Tested configurations (I)

HACE framework

Previous parameter tunning phase with a small dataset from subhierarchy *"[C] Diseases"*

1. Effectiveness of bottom-up positive example selection
   - random document selection *vs.* *k*-means based document selection
   - up to 500, 1000 and 2000 selected instances per node
2. Effectiveness of guided top-down classification
3. Usefulness of word bigram based features *vs.* single token features

Results

- *k*-means based document selection has better performance, but training time is almost twice
- better results using greater amounts of positive instances
- guided top-down search improved classification time and quality
- word bigrams did not appear to help

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Tested configurations (II)

Rebayct

1. Effectiveness of aggregating the results of 5 models *vs.* single model performance
2. Usefulness of word bigrams as instance features using a single Rebayct model

Conclusions

- marginal improvements when results of 5 Rebayct models were combined
- great improvement due to word bigram representation

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BioASQ Task 1A participation

Submitted configurations

- HACE1: HACE framework with
  - *k*-means bottom-up positive example selection (2000 documents per node)
  - IG as local feature selection (100 features)
  - SVM as local content based classifier
- HACE2: same as HACE1 employing a guided top-down search approach
- HACE2-NE: same as HACE2 using word bigrams as textual features
- REBAYCT: combination of 5 Rebayct models trained with 5 splits of the reduced training set
- REBAYCT2: single Rebayct model using word bigram alternative collection

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Conclusions

- Two different hierarchical text categorization systems evaluated in 2013 BioASQ challenge
- Quite far from top performance systems in the challenge, but some improvements were done from the original systems employed in first batch
- With minor changes our systems were able to deal with a problem larger than the ones that originated them
- Tested configurations and BioASQ challenge results give us some insights for improvement
- Large training data sets make unnecessary to employ sophisticated machine learning approaches?
  - Training text contribution in Rebayct classifications was more important than structural and descriptor label contributions
  - Guided top-down search in HACE employs a very simple kind of k-nn prefiltering.

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Future work

- Advanced NLP processing of documents and descriptor labels (POS tagging, NER, ...)

HACE framework

- Make a more deep parameter tunning
- Exploit the guided top-down search approach
- Exploit (and optimize) the context based ”routing” approach

Rebayct

- Evolve to a sort of active learning approach with better training document selection
- Exploit word bigrams and powerful text processing approaches to improve quality of input data