Automatic fine grained semantic classification for domain adaptation

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STEP 2008, Venice

Deriving domain-specific classes for verb arguments

- **Goal:** Obtain domain-specific semantic classes for verbs & their arguments
- **Why?**
  - Verb arguments important in NLP (WSD, ambiguity resolution) e.g. 'Flying planes can be dangerous' vs 'Swallowing apples can be dangerous'
  - WordNet & FrameNet often unable to cater for domain-specific senses
- **Our hypothesis:** Better to induce verb sense & semantic types automatically from the data of domain of interest
- **How:** Cluster verbs & their arguments simultaneously

Outline of the Talk

- Background to semantic classification
- Method for clustering verbs & their arguments to obtain semantic classes
- Interpretation of the semantic classes
- Results & Evaluation
- Future Work

Related Work

- Literature on acquiring semantic classes extensive
- Mainly motivated by WSD, clustering nouns or verbs
- Most relevant to our work:
  - [SchulteimWalde 2003] method for clustering German verbs by linguistically motivated feature selection
  - [Korhonen et al 2006] cluster verbs from biomedical domain
  - [Gamallo et al 2005] perform dual clustering of words and their lexico-syntactic contexts. Create lexicon of words & requirements applied to PP by clustering similar syntactic positions.
  - [Pustejovsky et al 2004] combine selection contexts for verbs to form CPA patterns semi-automatically.

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- Side effect: clustering verbs with similar slot
- Verb class induction: e.g. *'admit'*, *'deny'* clustered together if their arg share the same filler words (e.g. obj *'wrongdoing'*)

The Corpus & pre-processing

- **Domain of application:** Financial News
- **Corpus:** WSJ section of Penn Treebank II
- **Why?** Predicate-argument structures easily accessible.
- **Corpus Statistics:** 2454 articles (300,000 words), 2798 distinct verb predicates
- **Pre-processing:**
  - Obtained predicate-argument structures using [Liakata & Pulman 2002].
  - Boosting of low frequency verbs
  - Merging together arguments that are NEs: person names, companies, locations, numeric expressions etc.

Clustering argument slots of verbs (1)

We assume: Argument slots of predicates can be characterised by their filler words like a document is characterised by the words it contains.

VERB-ARG	FILLER WORDS/FREQ
invest-subj	person-394,company-86,investor-29,fund-20,..
invest-obj	money-204,person-172,percentage-80,price-36,..
invest-iobj	proposition-63,share-3,money-2,loan-2,..
give-subj	person-7519,company-1889,analyst-296,location-211,..
give-obj	person-605,percentage-350,money-261,agreement-86,..
give-iobj	proposition-610,person-6,money-4,offer-3,..

Therefore: To cluster verb-argument slots together, represent them using Vector Space Model (VSM) & compare their filler words

Clustering argument slots of verbs (2)

VERB-ARG	freq of FILLER WORDS as features			
	person	company	analyst	percentage ..
invest-subj	394	86	13	4..
invest-obj	173	43	0	82..
invest-iobj	1	0	0	0..
give-subj	7519	1889	296	43 ..
give-obj	605	45	9	350..
give-iobj	6	2	0	0

- A matrix containing all verb-arg slots (8,394) as rows and all possible word fillers (32,990) as columns is very sparse.
- Feature selection is required to reduce size of matrix.
- Clustering using **Autoclass**

Autoclass system

- [Cheeseman & Stutz 1995] is probabilistic clustering method.
- Autoclass is an extension of the mixture model as each instance can be characterised by multiple attributes
- Assumes instances of each cluster follow probability distribution
- Clustering problem is given number of clusters find the parameters of the distributions
- Input data in matrix format
- **Why Autoclass?**
  - Number of clusters/classes unknown
  - Probabilistic membership to multiple classes allowed

Clusters & their interpretation

- Best result: 32 classes, all verb-arg assigned deterministically
- **Class measures:** *strength, weight, cross-entropy*
- **Most influential features:** *the ones corresponding to precise concepts associated with specific contexts (freq*idf)*
- *Look at class members to interpret classes:*

```
class(9,[‘climb_arg1’,‘add_up_arg1’,‘shoot_arg1’,‘balloon_arg1’,
        ‘deflate_arg1’,‘decline_arg1’,‘crash_arg1’,
        ‘sink_arg1’,‘slump_arg1’,‘blossom_arg1’,‘blow_arg1’,
        ‘blow_up_arg1’,‘come_up_arg1’,‘boost_arg2’,
        ‘set_off_arg1’,‘break_arg1’,‘soar_arg1’,‘come_down’’,
        ‘slip_arg1’,‘bud_arg1’,‘build_up_arg1’,
        ‘bump_up_arg1’,..)
```

- Class 9 as **group of verbs**: Verbs showing sudden movement and numeric change.
- Class 9 as implicit **group of nouns**:‘Financial indicators’.

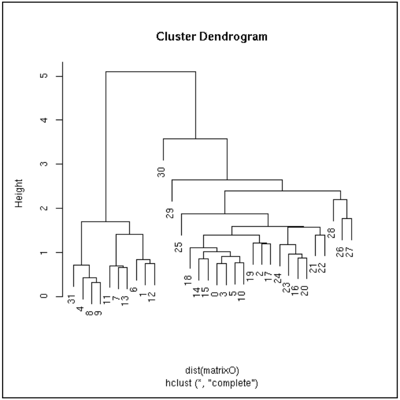
From noun clusters to semantic typing

- Nouns arg to several verbs therefore belong to more than one class. Look at **tf-idf** for most representative class for a term
- **Interpretation for each class:** highest ranking items by descending tf-idf

class	label
0	proposition
1	company_organisation
2	unspecified_someone
3	proposition_truth_profit_patient_impact
4	percentage_money_income_revenue_stock_share_asset
5	percentage_mony_numXpression
6	spokesman_company_person_analyst
7	income_revenue_net_rate_cost_stock
8	place_step_effect_loss_action
9	proposition_company_spokesman_revenue_analyst
10	proposition_stake_rate_percentage
11	proposition_percentage_sure_decision_bid
12	year_percentage_quarter_index
13	reporter_dividend_money_percentage_analyst
14	percentage_proposition_numXpression
15	proposition
16	percentage_stake_demand_money_rate_cash_capital
17	proposition_projection_rate
18	proposition_trading_pressure
19	proposition_table_corner_board_tide
20	proposition_percentage_public_private_high_low
21	government_civilian_unspecified
22	proposition_unspecified_game_role_cash_company
23	percentage_proposition_numXpression
24	percentage_proposition_date_profit
25	director_court_partner_company
26	proposition_contract_profit_demand_requirement
27	demand_problem_leak
28	year_month_time
29	proposition_money_percentage_share_stock
30	year_time
31	fund_proposal_investor

Hierarchy for semantic typing

- Obtaining semantic type/labels for classes non-trial because of overlap
- Hierarchical clustering with overlap coefficient: $sim(A, B) = \frac{|A \cap B|}{min(|A|, |B|)}$



From semantic classes to patterns

- To facilitate the use & evaluation of classes for semantic type assignment, we automatically created verb patterns:

ARG1 **VERBv** (ARG2) (ARG3)

- 'One sense per corpus' assumption, one pattern for each verb
- Patterns modelled on CPA patterns [Pustejovsky et al 2004]
- For example:
  1 report 4 (10) equivalent to:

  [*company_organisation*] **report**
  [*percentage_money_income_revenue_stock_share_asset*]
  [*proposition_stake_rate_percentage*]

Example: patterns used to assign semantic types

Example: *'That is the first time both indexes dropped by double-digit percentages.'*

- **Text to assign semantic type to:** *'indexes dropped by percentages'*
- **relevant pattern:** *[9 drop 8 28]*
- **Check:** *Does 'index' have class 9? Does 'percentage' have class 28?*
- **Check:** *How 'close' are class 9 & the actual class of 'index'?*

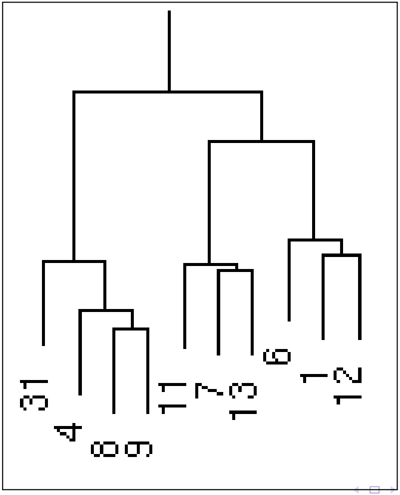
Algorithm for the evaluation of semantic patterns

- Preliminary evaluation on two articles **WSJ, FT** March 2008
- Parsed the articles using CC-Tools, obtained **subj**,**obj** and **iobj** dependencies → evaluation set

For each verb-argument pair token in the evaluation set:

1. Look for a pattern in the database for that verb (Recall cnt + 1)
2. Obtain the type that the pattern assigns to the argument
3. Get the correct type (3 with highest freq out of 10 with highest tf-idf)
4. If type assigned matches any of the 3 classes-semantic types,assignment correct.
5. Otherwise look at cluster dendrogram and find distance btw correct and returned types.
6. Proceeded to the next verb-argument pair.

Subsection of the class dendrogram



Example: evaluation of assignment

- **Example 1:** *'The index is calculated using mortgage loans of $417,000 or less.'*
- **Example 2:** *'Ofheo oversees the government-sponsored mortgage-finance companies Fannie Mae and Freddie Mac'.*

RASP-like dependencies (ncsubj, dobj, iobj) generated by CC-tools:

```
dobj using_4 loans_6
dobj oversees_1 Mae_7
ncsubj oversees_1 Ofheo_0
dobj oversees_1 Mac_10
```

The patterns: Ex1: [6 use **4** 14]   Ex2: [**12** oversee **13** 15]

- Ex1: For 'loan' the correct class is (4,7,11) -**Correct!**
- Ex2: For 'Ofheo' the correct class is (7,12,4) -**Correct!**
- Ex2: For 'Mac','Mae' the correct class is (6,9,1) -*Wrong.*

Results

	verbs	verb-arg	recall	exact match
WSJ	46	78	78/78	33/78 (43%)
FT	24	53	53/53	21/53 (39.6%)

	distance 1	distance 2	distance 3
WSJ	41/78 (53%)	55/78 (70.5%)	60/78 (76.9%)
FT	26/53 (49%)	30/53 (56.6%)	33/53 (62.2%)

Conclusion & Future Work

- Method for for **automatically acquiring domain-specific selectional restrictions for verbs**
- Promising initial results
- Extend to biomedical domain
- Obtain parses and LFs for new texts (using CC-tools and Boxer)
- Try different clustering method and feature selection

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Acknowledgements

Thanks to Rachele de Felice for her assistance, Stephen Clark & Rada Mihalcea for their useful comments.

This work was partially funded by:

- the Companions project (`http://www.companions-project.org`)
- the ART Project (`http://www.aber.ac.uk/compsci/Research/bio/art/`)