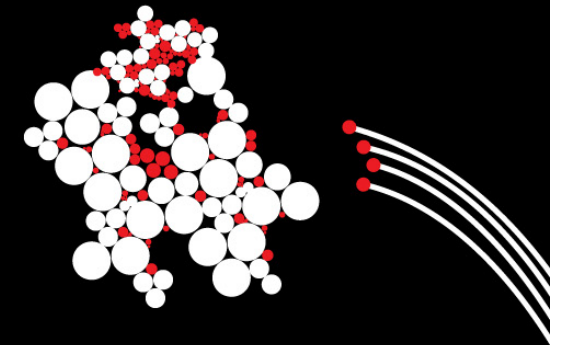


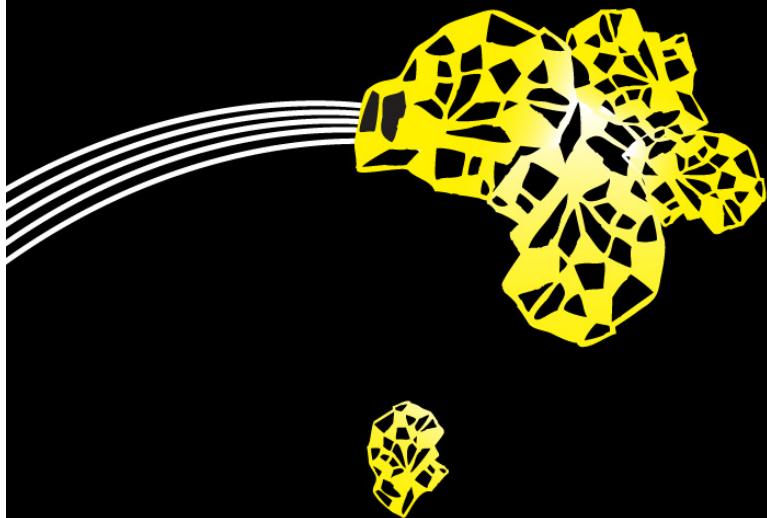
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# Concept Extraction Challenge: University of Twente at #MSM2013

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Database Chair



# Agenda

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- Introduction.
- Named Entity Extraction:
  - SVM.
  - CRF.
  - Hybrid approach.
- Named Entity Categorization :
  - Named Entity Disambiguation.
  - Entity Categorization.
- Results.
- Conclusion.

# Introduction

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 NewsHour @NewsHour .../wiki/South\_Island .../wiki/New\_Zealand 18 Nov 10  
RT @breakingnews: Blast in South Island, New Zealand,  
coal mine leaves 30 miners unaccounted for - Reuters  
Expand LOC LOC Org  
.../wiki/Reuters

Name Entity  
Recognition

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Name Entity  
Extraction

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Name Entity  
Categorization

Name Entity  
Categorization

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Name Entity  
Disambiguation

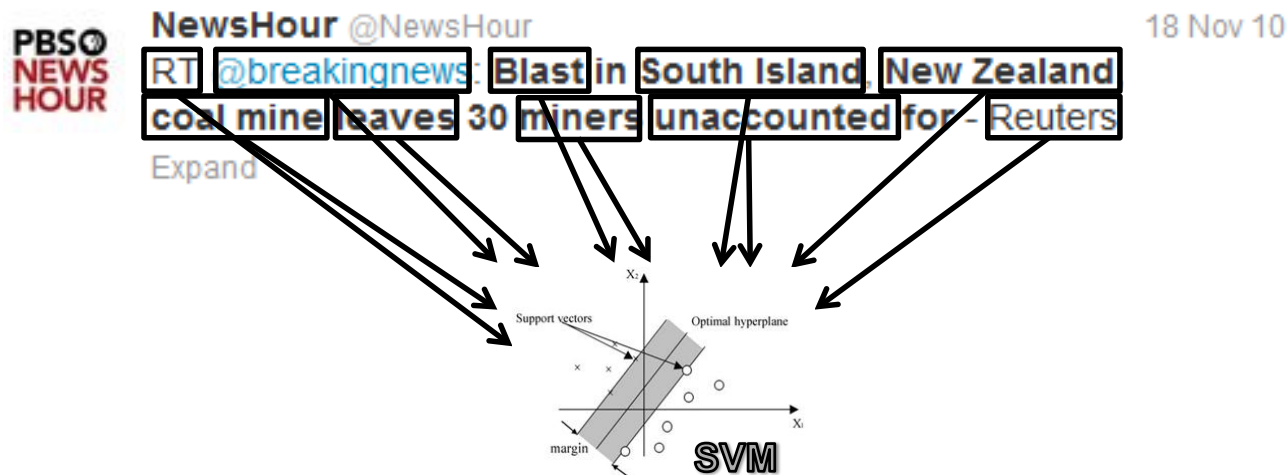
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Entity  
Categorization

# Named Entity Extraction

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- SVM:
  - Use TwiNER (Li et al @ SIGIR 2012) approach for segmenting tweet.
  - Yago KB is also used to enrich the NE candidates to achieve high recall.
  - Some hypothesis are applied to improve precision (removing stop words & verbs)



- Different features are extracted for each segment to train and test the SVM (like POS, AIDA disambiguation score, MS Web-Ngram probability, Shape features, frequency, etc.)

# Named Entity Extraction

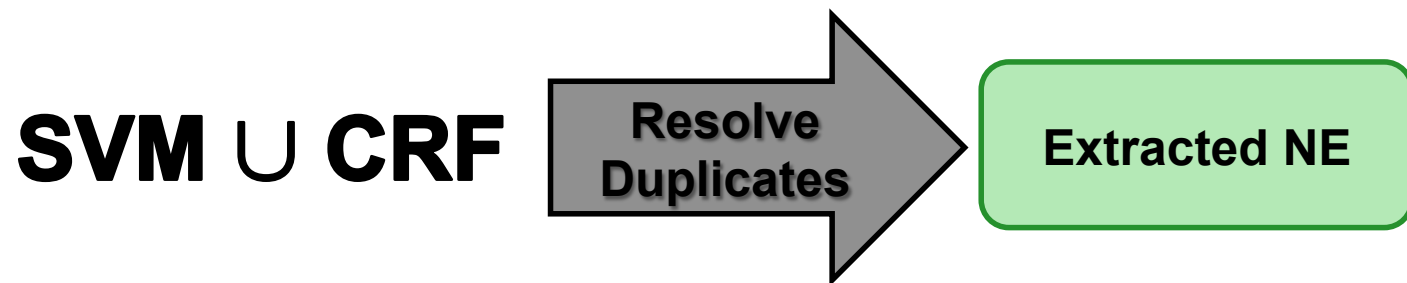
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- CRF:
  - CRF is popular for sequence labeling. But training of CRFs can be very expensive due to the global normalization (linear-chain CRFs):
    - **quadratic** in the size of the label set and almost **quadratic** in the size of the training sample
  - We used method called *empirical training*.
    - The maximum likelihood estimation (MLE) of the *empirical training* has a closed form solution, and it does not need iterative optimization and global normalization. (Fast!)
    - The MLE of the *empirical training* is also a MLE of the standard training. (Precise!)
- Tweet text is tokenized. For each token, the following features are extracted and used to train the CRF:
  - The Part of Speech (POS) tag of the word.
  - The word shape.

# Named Entity Extraction

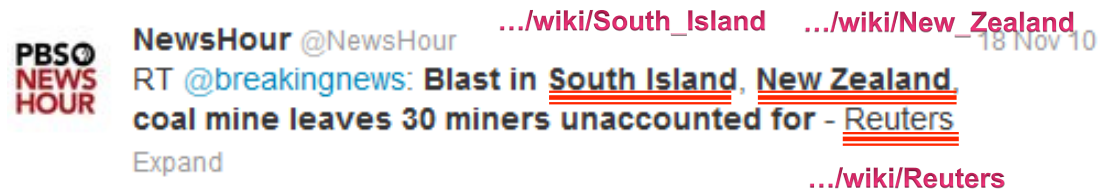
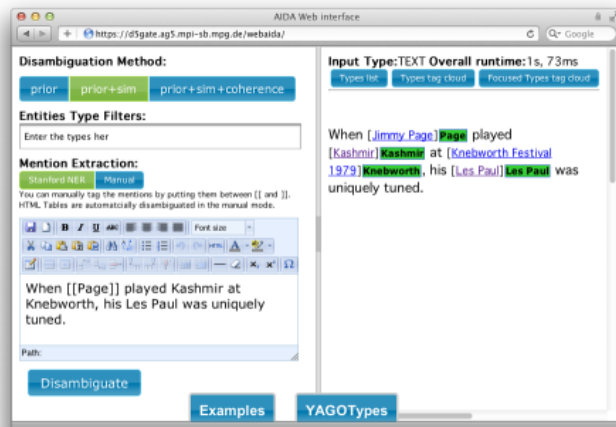
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- Hybrid approach:
  - We take the union of the CRF and SVM results, after removing duplicate extractions, to get the final set of annotations.
  - For overlapping extractions we select the entity that appears in Yago, then the one having longer length.



# Named Entity Categorization

- Named Entity Disambiguation:
  - AIDA disambiguation system is used to disambiguate the extracted NE.
  - ~75.8% of training data NEs  $\in$  YAGO KB.
  - For NEs  $\notin$  YAGO, we look for the first token in the NE if it  $\in$  YAGO, if found we pick the entity with the higher prior probability. (Ex: “*Sara MacDonald*” is assigned to “.../wiki/Sara\_Sidle”)
  - Other NEs  $\notin$  YAGO at all are assigned to --NME--.



# Named Entity Categorization

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- Entity Categorization:
  - We build a profile for each category (PER, LOC, ORG, and MISC) from the Wikipedia Categories of each disambiguated entity.
  - If (NE  $\in$  Training set)  $\rightarrow$  Use category with the highest prior probability;
  - Else if (NE assigned to an entity)  $\rightarrow$  Find the most similar category profile to the Wikipedia Categories of the disambiguated entity;
  - Else  $\rightarrow$  Assign NE to PER category; //used with 2.8% of the extracted entities.



# Results

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- 4-fold cross validation.

Extraction Results

|  | <b>Pre.</b> | <b>Rec.</b> | <b>F1</b>     |
|--|-------------|-------------|---------------|
| <b>Twiner Seg.</b>                         | 0.0997      | 0.8095      | 0.1775        |
| <b>Yago</b>                                | 0.1489      | 0.7612      | 0.2490        |
| <b>Twiner<math>\cup</math>Yago</b>         | 0.0993      | 0.8139      | 0.1771        |
| <b>Filter(Twiner<math>\cup</math>Yago)</b> | 0.2007      | 0.8066      | 0.3214        |
| <b>SVM</b>                                 | 0.7959      | 0.5512      | 0.6514        |
| <b>CRF</b>                                 | 0.7157      | 0.7634      | 0.7387        |
| <b>CRF<math>\cup</math>SVM</b>             | 0.7166      | 0.7988      | <b>0.7555</b> |

Extraction and Classification Results

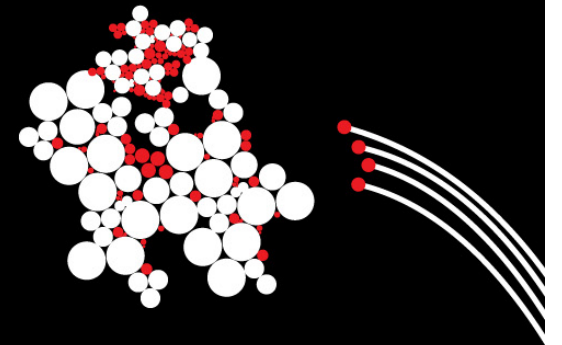
|  | <b>Pre.</b> | <b>Rec.</b> | <b>F1</b>     |
|--|-------------|-------------|---------------|
| <b>CRF</b>   | 0.6440      | 0.6324      | 0.6381        |
| <b>AIDA Disambiguation<br/>+ Entity Categorization</b> | 0.6545      | 0.7296      | <b>0.6900</b> |

# Conclusion

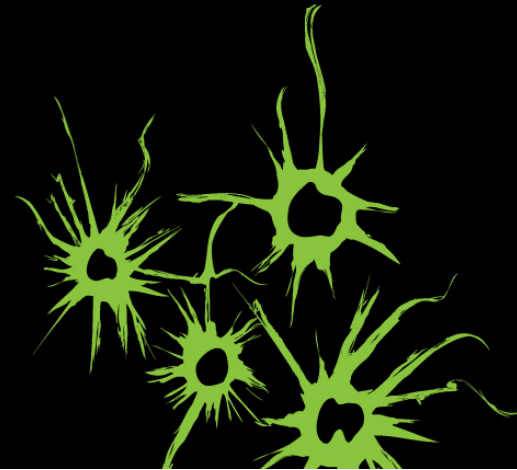
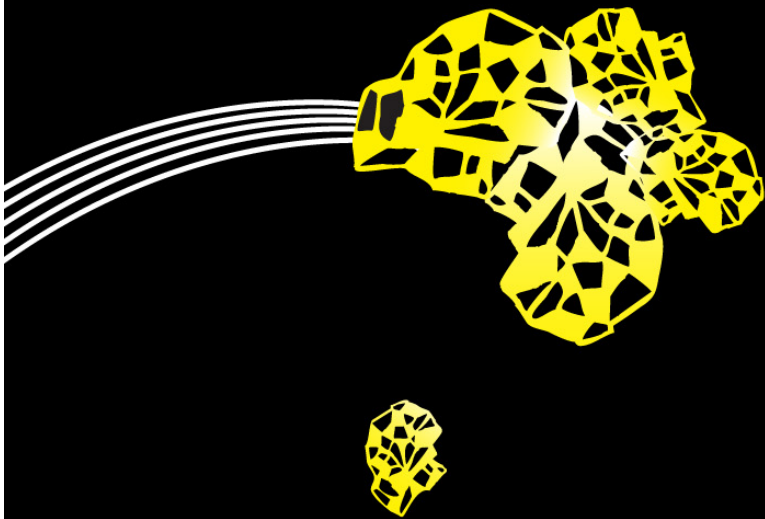
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- We split the NER task into two separate tasks:
  - NEE which aims only to detect entity mention boundaries in text.
  - NEC which assigns the extracted mention to its correct entity type.
- For NEE we used a hybrid approach of CRF and SVM to achieve better results.
- For NEC we used AIDA disambiguation system to disambiguate the extracted named entities and hence find their type.

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Thank You



## Cases where SVM extracts other NE than CRF

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217: "\_Mention\_ : Joy ! **MS Office** now syncs with **Google Docs** -LRB- well , in beta anyway -RRB- . We are soon to be one big happy collaborative Click family . *Ric*"

245: "\_Mention\_" `` valleylist "" v135 r. 1 - - electricity -LRB- **jerry yang** and david filo -RRB- <NEWLINE> \_URL\_ "

**Bold** → SVM

*Italic* → CRF