13th ICCRTS: C2 for Complex Endeavors

Semantic Machine Understanding

Topic 9: Collaborative Technologies

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Abstract

Semantical Machine Understanding is the foundation for automatic sense and decision making of multinational, multicultural, and coalition applications. We show an innovative semantic machine understanding system that can be installed on each node of a network and used as a semantic search engine. Innovations of such a system include

1) text mining
2) meaning learning
3) collaborative meaning search

In this paper, we also show the feasibility of using a semantic search architecture and discuss the two ways it is drastically different from current search engines:

1) indexes embedded in agents are distributed and customized to the learning and knowledge patterns of their own environment and culture. This allows data providers to maintain their own data in their own environment, but still share indexes across peers;
2) Semantic machine understanding enables discovery of new information rather than popular information.

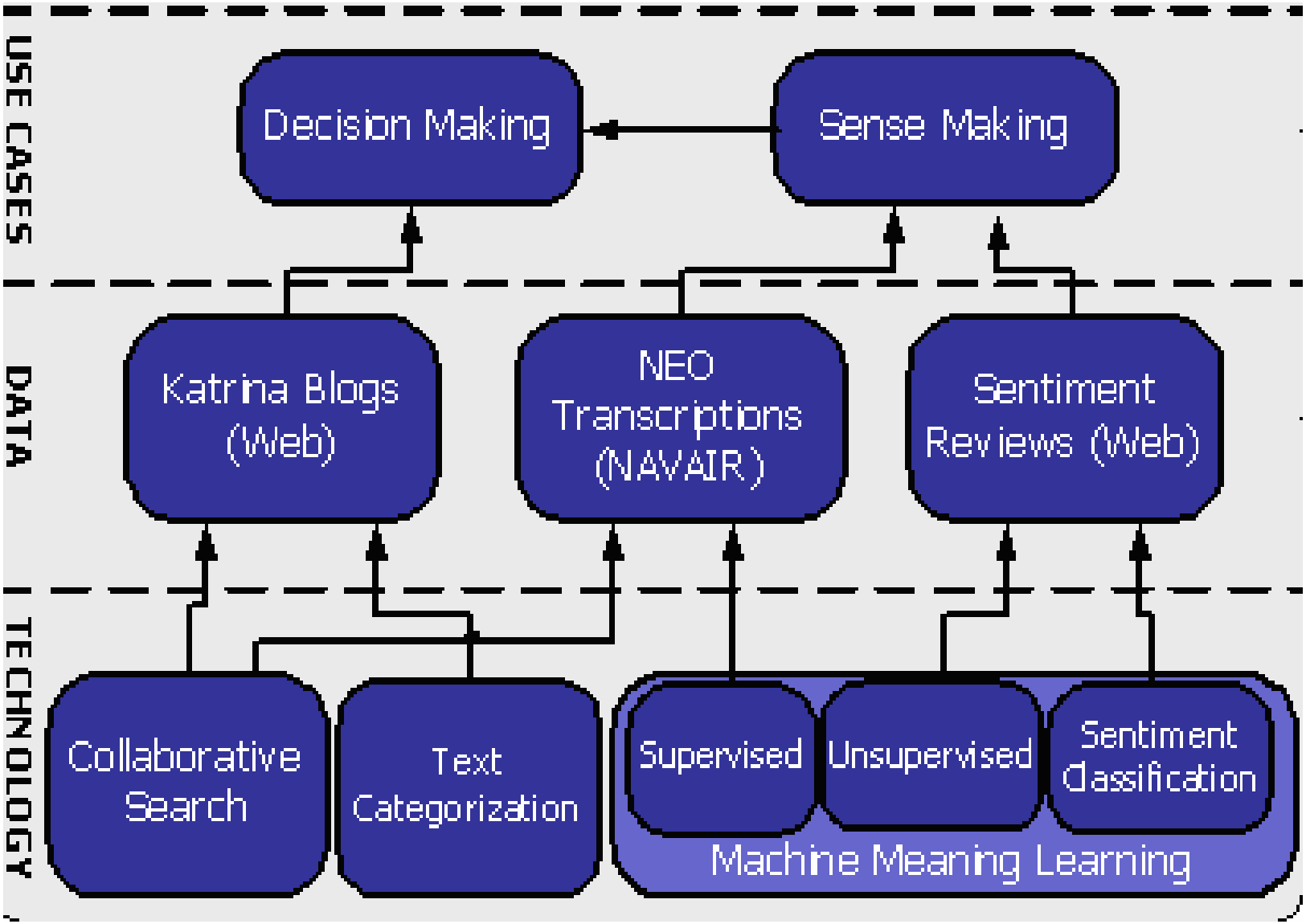
Background

- Joint, coalition, non-Government and volunteer organizations working together require analysis of open-source data.
- Requires capability for the automated understanding
- Requires semantic understanding and search in language/culture free environment
  - Not to use linguistic based approaches.
  - Many available tools for text analysis such as entity extractions are mostly based on linguistic models to identify entities.
- Needs advanced search engines for information search and retrieval. Need to share distributed indexes, culturally diverse search indexes
- Needs peer-to-peer (P2P) technologies to store, locate and understand information with agent-like applications
  - fault-tolerate, distributed and self-scalable

Objectives

- Demonstrate the capabilities of a semantical machine understanding system in
  - three (3) data sets:
    - NEO transcriptions from NAVAIR
    - Katrina Blogs,
    - Sentiment reviews from web
  - two (2) use case areas:
    - decision making
    - sense making.
- Samples of historical data
  - Observations: free-text, open vocabulary sentences
  - Meaning: the corresponding meaning of the observations above made human analysts using keywords or also free-text, open vocabulary sentences

Semantic Machine Understanding: Overview

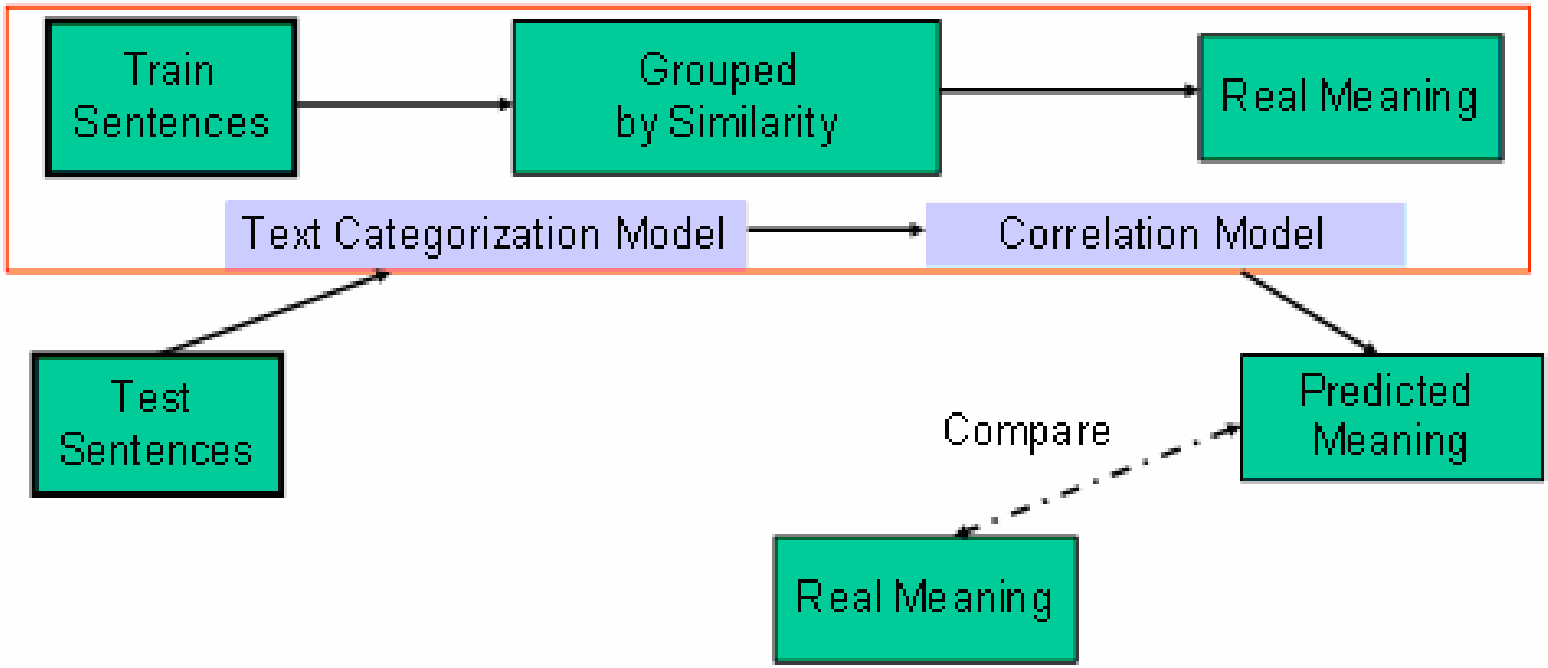


Semantical machine understanding: Tree Components

- Text mining: extracts concepts and meaning clusters from free text input based on contexts using statistical pattern recognition.
- Meaning learning: discover knowledge patterns that link human labeled meaning to raw text observation. The knowledge patterns are applied to predict the meaning of new data.
- Collaborative meaning search: incorporates humans and machines in a loop to form a collaborative network and enhance the meaning iteratively.

Machine Learning

- Train set
  - Samples of the human labeled meaning of sentences
- Test set
  - Left out samples



Use Case 1: Sense Making Using NEO Transcription Data

- The Noncombatant Evacuation Operation scenario, three face-to-face NEO scenario transcripts(FS-2, FS-3, and FS-4) from NAVAIR as shown in Figure 3.
  - The text observations: the team communications and conversations, i.e. transcripts.
  - The meaning are pre-defined macro-cognitive stages and states (processes).
    - The stages: categories of communications such as “Knowledge Construction (KC) “Team Problem Solving”.
    - The states (processes): alternative categories such as “individual task knowledge development”, “iterative information collection and analysis”, etc.
- Important questions that psychologists try to answers are:
  - Can these stages and states (processes) be predicted from transcripts?
  - How to track and identify these processes automatically?

NEO Transcription Data

Sample data of three teams
•FS-2, FS-3, FS-4

CASC Phase 2:
Face to Face – Static (FS-2)
03/03/04

Scribe: I

Subjects: FS-2-E, FS-2-I, FS-2-W

#	Subject	Start Time	Content	Stop Time	Stage	State
1	E	1:05	All right… um…	1:06	MISC	09
2	I	1:08	Does anybody have any ideas?	1:09	TPS	09
3	W	1:15	First think I think we have to think about is when we want to do that, and it said that, um, it's really foggy during the morning time and then it gets completely clear by noon, so we probably want to do it somewhere between, you know, 2 am and when it gets real clear during the day so that we're not easily detected, or whatever.	1:37	TPS	02
4	I	1:37	OK	1:38	TPS	12
5	E	1:41	So you say it's going to be easier to do it during, like, nighttime?	1:46	TPS	03
6	W	1:46	Well, if we don't want to be seen and we know, like, we know where we're going, and we can get there, when it's like foggy outside so nobody will see…	1:55	TPS	01
7	E	1:54	Oh, ok. I see what you mean.	1:56	TPS	12

Explored different settings for learning and predicting the meaning of sentences.

- Setting 1: Train FS-3 and Test FS-3
- Setting 2: Train FS-3 and Test FS-2
- Setting 3: Train FS-2 and FS-3, Test FS-4
- Add features gradually
  - Use content only
  - Use content and features (body languages, questions, statements, etc.)
  - Use content, features and previous states

Setting 1

Table 1: State Prediction Test Result 1

Setting 1:Train FS-3; Test FS-3	Content	Content Features	Content Features Previous States
Overall	**30%**	**35%**	**49%**
State 3: individual task knowledge development		44%	
State 12: convergence of individual mental models to team mental model	80%	85%	58%
State 6: individual visualization and representation of meaning	58%	46%	
State 4: team knowledge development			71%
State 10: team shared understanding development			80%
State 8: knowledge interoperability development	48%	45%	48%
State 9: iterative information collection and analysis			40%

Setting 2

Table 2: State Prediction Test Result 2

Setting 2: Train FS-3; Test FS-2	Content	Content Features	Content Features Previous States
Overall	**20%**	**31%**	**48%**
State 3: individual task knowledge development		44%	69%
State 12: convergence of individual mental models to team mental model	82%	40%	42%
State 6: individual visualization and representation of meaning	50%	57%	57%
State 4: team knowledge development			76%
State 10: team shared understanding development			66%
State 8: knowledge interoperability development		48%	
State 9: iterative information collection and analysis			

Setting 3

Table 3: State Prediction Test Result 3

Setting 3: Train FS-2 and FS-3; Test FS-4	Content	Content Features	Content Features Previous States
Overall	**30%**	**30%**	**50%**
State 3: individual task knowledge development	72%	40%	81%
State 12: convergence of individual mental models to team mental model	67%	63%	41%
State 6: individual visualization and representation of meaning	50%		50%
State 4: team knowledge development			76%
State 10: team shared understanding development			85%
State 8: knowledge interoperability development			
State 9: iterative information collection and analysis			44%

Add Collaborative Meaning Search

Table 5: State Prediction Using Collaborative Meaning Search

Setting 1:Train FS-3; Test FS-3	Content	Content + Features	Content +Features+Previous States	Collaborative Meaning Search
Overall	**30%**	**35%**	**49%**	**54%**
State 3: individual task knowledge development		44%		44%
State 12: convergence of individual mental models to team mental model	80%	85%	58%	72%
State 6: individual visualization and representation of meaning	58%	46%		62%
State 4: team knowledge development			71%	74%
State 10: team shared understanding development			80%	72%
State 8: knowledge interoperability development	48%	45%	48%	52%
State 9: iterative information collection and analysis			40%	

Stage Prediction

Table 4: Stage Prediction Result

Setting 1:Train FS-2; Test FS-2	Content	Content Features Previous Stages	Content Features Previous Stages Prediction	Content POS Tags
Overall	**61%**	**74%**	**61%**	**65%**
KC	6%	60%	38%	44%
TPS	91%	80%	72%	80%

Summary for NEO

- Correlation between transcripts and cognitive states/processes are low in general
- Adding more features is helpful
- Adding collaborative search is more effective

Use Case 2: Decision Making Using Katrina Blogs

- Katrina disaster management in August 2005 Collected approximately 300 blog entries from 8/28 to 8/31, 2005). Blog entries are dynamic, real-time data that are used to compensate for “official” data.
- Example for decision making decide on transportation, for example, “helicopter” and “boat”.
  - The search returns the numbers of matches from the two official repositories, a simple decision goes for a helicopter since it has more matched capability and knowledge. However, when adding blogs as the new repository, found a few distinct and meaningful categories that:
    - Confirm and corroborate the current official information: helicopters are performing rescuing jobs.
    - Discover new information: the number of helicopters was very limited (only four were used in rescue) and people were shooting at them.
    - Discover new information: helicopters might have fuel concern since all the gas stations are not available.
  - Decision changes

What does a real-life relief effort look like? Java Earthquake Relief Effort

International Disaster Relief Effort (PACOM)

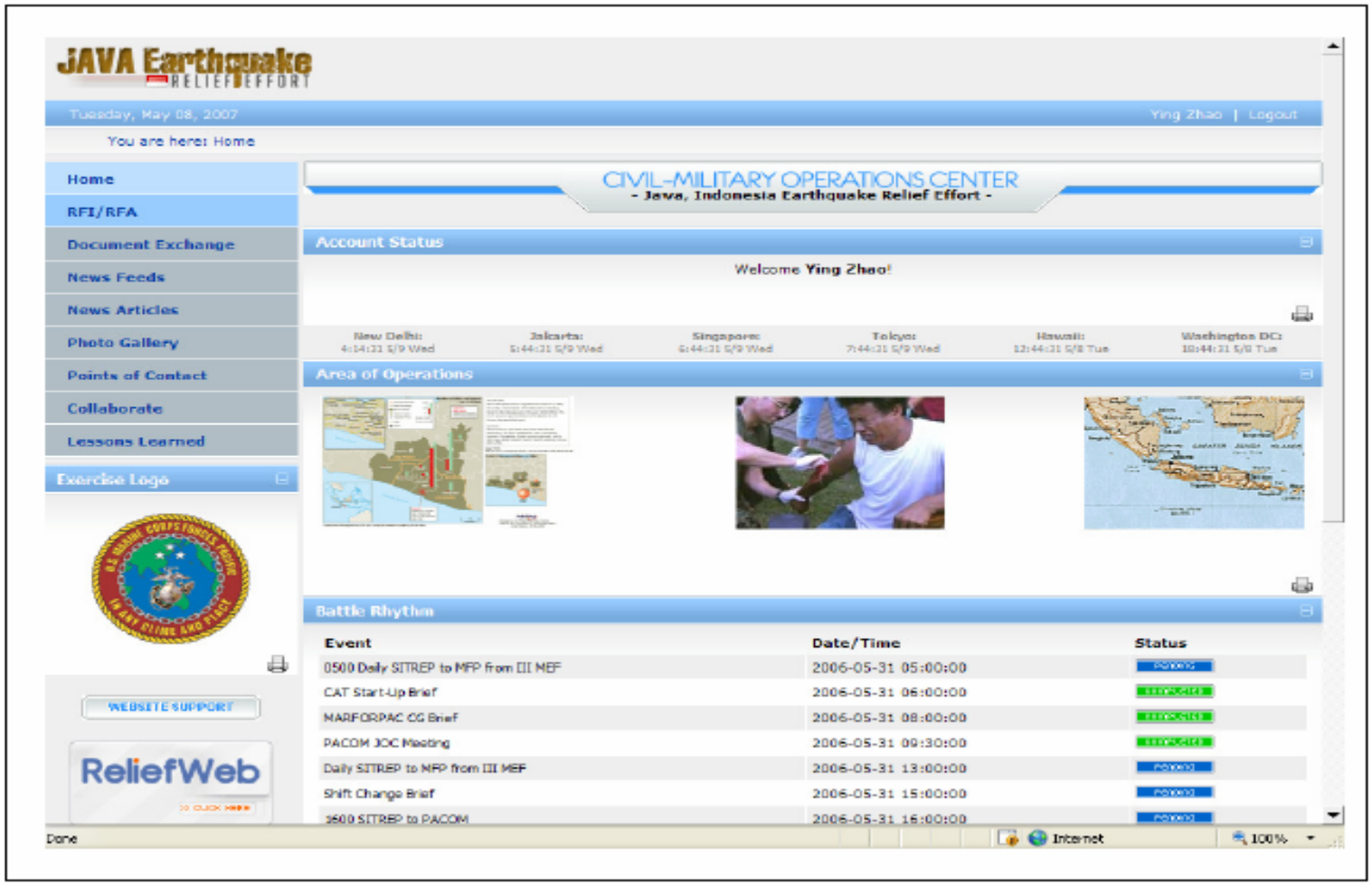


Figure 4. Java Earthquake Relief Effort Website

Real-life Relief Operation

Organizations

- PACOM
  - United States Pacific Command
- MARFORPAC
  - Marine Forces Pacific
- III MEF
  - Marine Expeditionary Force

Information Types

- SITREPs
  - TXT, DOC
- Message/Orders
  - TXT, RTF
- Reports/Briefs
  - PPT
  - *Information: Template of information required (battle rhythm, overview, significant events, G-X, protocol, concerns/issues)*
- News
  - News from feeds (e.g. Yahoo feed)
  - HTML
- RFI/RFA
  - Request for Military Assistance
  - *How this ties to the process?*

Real-life Relief Operation Requirement

Available Data

Organization/Information Type	SITREPs	Messages/Orders	Reports/Briefs
PACOM		x	
MARFORPAC			
III MEF	x		x

Information Type	Available
Articles	
News	Many
RFI/RFA	

Reference Websites

- USAID
  - Relief effort help; includes some data sheets
- US Department of State
  - Information on Indonesia
- World Bank Group
  - Information on Indonesia
- CIA World Fact Book
  - Information on Indonesia
- WHO (World Health Organization)
  - Situational Reports

Processes in a real-life emergency operation

- Steps
  - Step 1: gather/store information (SITREPs, RFA, websites, news, etc...)
  - Step 2: visualize data
  - Step 3: present data to decision makers (SITREPs, briefings)
  - Step 4: communicate decision (orders)

Orders are the decisions communicated to everyone and provide authority using the structured United States Message Text Format (USMTF)

  - Step 5: action (RFAs)
- Where does semantical machine understanding fit?
  - Information gathering (SITREPs, RFA, websites, news, etc), data presentation and decision making
  - The diversified document types and collaborative partners require a semantic search engine to interpret the meaning and decide the value of a piece of information and reduce manpower

Movie Review Data Set

- In order to illustrate the process, we use a public data set
  - 5331 positive
  - 5331 negative movie review sentences from

http://www.cs.cornell.edu/people/pabo/movie-review-data)

Sentiment Classification and Unsupervised Learning

- A semantic search for decision making, the key factor is to decide what's the meaning given a piece of.
- Sentiment Classification
  - label meaning as "positive" or "negative", "good" or "bad", "pros" or "cons" (to a decision, for example). Recent years have seen rapid growth in on-line discussion groups
    - product review sites
    - overall opinion towards a decision of subject matter.
  - Related to semantical understanding and text categorization, however, difficult since it is to predict human cognition.

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Apply an iterative algorithm to improve sentiment classification and decision making

- Step 1: Start with a very short human labeled sentiment word list labeled positive or negative
- Step 2: Decide a sentence's sentiment by counting how many positive or negative words from the short list appearing in a sentence. If more positive words than negative, the whole sentence is tagged positive
- Step 3: Extract a long list of words characterizing the meaning clusters in the whole data set. The list is discovered by the ccc algorithm.
- Step 4: For each word in the long list, estimate how likely it appears in the same sentence with the "positive" or "negative" words in the short list. Decide a word "positive" in the long list if it is more likely to associate with the positive words in the short list; "negative" otherwise.
- Step 5: Decide the sentences' sentiment using the same decision rule in Step 2 and the long list generated from Step 4.
- Step 6: Iterate Step 4 and 5 a few times where the short and long list are merged as one, however the sentiment predictions are improved every iteration until they converge.

Table 6: Iterative and Unsupervised Sentiment Classification of Movie Reviews

Accuracy	Step 2	Step 5	Step 6 (iteration 1)	Step 6 (iteration 10)
	52%	54%	59%	80%

Conclusions

- Demonstrated the feasibility for an innovative Semantical Machine Understanding system on three data sets and two use cases of sense making and decision making.
- The key contribution
  - applied combined innovations in text mining, meaning learning and collaborative meaning search to construct a semantic search architecture
  - improved sense and decision making for multinational, multicultural, and coalition applications.

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