More than Just Words: Discovering the Semantics of Text with a Minimum of Supervision

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We want to assign semantic meaning to content:

- **Text**
- Speech
- Images
- Video
- Audio, ...

E.g., in the form of **semantic labels** => assist in search, mining, aggregation, summarization, ... of information
Text categorization

Google injects search savvy into display ad system
By MICHAEL LIEHTKE, AP Technology Writer - Fri Sep 19, 2008 4:20AM EDT

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Sanofi buys Merck's half of animal health business

By LINDA A. JOHNSON, AP Business Writer - 23 mins ago

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The move was required by regulators before Merck can close its $41 billion purchase of New Jersey neighbor Schering-Plough Corp., which also sells animal health products.

Sanofl, a joint venture founded in 1997, sells two widely used pet medicines, flea-and-tick blocker Frontline and chewable heartworm preventer Heartgard. It also sells Ivermect, which kills parasites in hogs and cattle, and other medicines and vaccines for livestock.

Report: Gender tests on runner done in SAfrica
AP - 2 hrs 33 mins ago
JOHANNESBURG - A South African newspaper has published what it says are e-mails showing local track officials authorized gender tests done in the country on runner Caster Semenya. Full Story »
Opinion recognition

**Land Rover Range Rover Sport** Massively improved, right up there with the nicer sporty-SUVs.

Just one thing: it’s not a Range Rover. The best Evo ever, Makkinen included. But at 50,000 you’ve REALLY got to want one.

Mining: dashboard
Relation recognition

Search of a database

SELECT COMPANY
FROM ACQUISITION
WHERE ACQUIRER = 'Google'

S1: Search engine giant Google has bought videosharing website YouTube in a controversial $1.6 billion deal.
S2: The companies will merge Google's search expertise with YouTube's video expertise, pushing what executives believe is a hot emerging market of video offered over the Internet.
S3: Google has acquired social media company, YouTube for $1.65 billion in a stock-for-stock transaction as announced by Google Inc. on October 9, 2006.
S4: Drug giant Pfizer Inc. has reached an agreement to buy the private biotechnology firm Rinat Neuroscience Corp., the companies announced Thursday.
S5: He has also received consulting fees from Alpharma, Eli Lilly and Company, Pfizer, Wyeth Pharmaceuticals, Rinat Neuroscience, Elan Pharmaceuticals, and Forest Laboratories.
Semantic role labeling

Recognizing the basic event structure of a sentence ("who" "does what" "to whom/what" "when" "where", ...)

fall.01
Arg1: Logical subject, patient, thing falling
Arg2: Extent, amount fallen
Arg3: Start point
Arg4: End point, end state of Arg1
Ex1: [Arg1 Sales] fell [Arg4 to $251.2 million] [Arg3 from $278.7 million].
Ex2: [Arg1 The average junk bond] fell [Arg2 by 3.7%].

By how much has fallen the average junk bond?

Question answering search
Temporal relation recognition

Reconstruct the temporal sequence of events in a story
Classical approaches

- Parsing of text based on hand-coded **symbolic patterns**
- **Supervised learning of the patterns** based on annotated training data
- Typical features to describe the patterns:
  - Lexical features: unigram, bigram, ..
  - Syntactic features: Part-Of-Speech, dependency tree
  - Semantic features: obtained from knowledge resource or other extractions
  - Discourse and pragmatic features
What is the problem?

- Supervised techniques yield good results
- But, need a manual effort, which can be substantial given:
  - Many different semantic labels
  - Many languages, domains, etc.

- But results could be improved:
  - Large variation of patterns that have a similar meaning: low recall
  - Patterns are often ambiguous: low precision
Too much variation

Google owns YouTube
Google has acquired YouTube
YouTube is bought by Google

...
Too ambiguous

- The meaning of a word depends on the company it keeps

Take a right at the green plant which produces solar energy.

Tom Mitchell Center for Automated Learning and Discovery.
Can we learn patterns for the semantic labeling with a minimum of supervision taking into account the large variation of patterns and ambiguity?

In the following we focus on text, but many approaches can be ported to other media.
Possible approaches (not exhaustive)

1. Examples are intelligently chosen by the machine and annotated by a human
2. Examples are automatically selected by the machine and annotated by the machine
3. A classifier is trained from labeled and unlabelled examples
4. We use few examples for training, but use additional constraints
5. We use few examples for training, but perform a constrained expansion
6. Multimodal processing
1. Examples are intelligently chosen by the machine and annotated by a human

Active learning

Labeled Seeds

Class A

Class B

Class B

Class C

Class C

Class C

Unlabeled Examples

?
Opinion recognition

The movie really seems to be spilling the beans on a lot of stuff we didn’t think we hand if this is their warm up, what is going to get us frothing in December

- de grote merken mogen er dan patserig uitzien en massa's pk hebben maarals de bomen wat dicht bij elkaar staan en de paadjes steil enbochtig, dan verkies ik mijn Jimny.

+ L’é tro bel cet voitur Voici tt ce ki me pasione ds ma petite vi!!!é tt mé pote é pl1 dotre truk!!!Avou de Dcouvrir

Mining: dashboard
Active learning for opinion recognition

- Selection of examples:
  - Uncertainty sampling: examples for which the current classifier assigns a class with low probability or confidence [Lewis & Catlett ICML 1994] [Tong & Koller JMLR 2001]
  - Redundancy and diversity sampling [Baram et al. ICML 2003]
  - Relevance sampling: to obtain more examples from a certain category
  - ...
Active learning for opinion recognition

Best results for classifying sentences as positive, negative or neutral with regard to an input product name on English blogs (e.g., skyrock.com, live-journal.com, xanga.com, blogspot.com, forums.automotive.com):

- Combination of:
  - **Random sampling** (to obtain some diversity of the patterns)
  - **Uncertainty sampling** (distance to the hyperplane found by Support Vector Machine): side effect: *reduction of redundancy*
  - **Relevance sampling**

  => less annotation and same accuracy

[Boiy & Moens IR 2009]
2. Examples are automatically selected by the machine and annotated by the machine

- World Wide Web = huge source of unlabeled examples!
- Relation extraction:
  - Search sentences on the Web:
    - containing 2 entities for which target relation holds => positive bag, but might contain some negative examples
    - containing 2 entities for which target relation does not hold => negative bag, assumed to contain only negative examples
  ⇒ input for Multiple Instance Learning algorithm

[Bunescu & Mooney ACL 2007]
+/$S_1$: Search giant Google has bought video-sharing website YouTube in a controversial $1.6$ billion deal

-/$S_2$: The companies will merge Google”s search expertise with YouTube”s video expertise, pushing what executives believe is a hot emerging market of video offered over the internet

+/$S_3$: Google has acquired social media company, YouTube for $1.65$ billion in a stock-for-stock transaction as announces bv Google Inc. on October 9, 2006

+/$S_4$: Drug giant Pfizer Inc. has reached an agreement to buy the private biotechnology form Rinat Neuroscience Corp., the companies announced Thursday.

-/$S_5$: Ha has also received consulting fees from Alpharma, Eli Lilly and Company, Pfizer, Wyeth Pharmaceuticals, Rinat Neuroscience, Elan Pharmaceuticals, and Forrect Laboratories
Subsequence kernel for relation extraction
[Bunescu & Mooney NIPS 2006] adapted with weighting scheme that takes into account frequency of a word (SSK-T2)

\[
\begin{align*}
 rK(s, t) &= fbK(s, t) + bK(s, t) + baK(s, t) \\
 bK_i(s, t) &= K_i(s_0, t_0, 1) \cdot c(x_1, y_1) \cdot c(x_2, y_2) \cdot \lambda(x'_0) + l(t'_0) \\
 fbK(s, t) &= \sum_{i,j} bK_i(s, t) \cdot K_j(s_f, t_f), \quad 1 \leq i, \ 1 \leq j, \ i + j < f_{b_{\text{max}}} \\
 bK(s, t) &= \sum_i bK_i(s, t), \quad 1 \leq i \leq b_{\text{max}} \\
 baK(s, t) &= \sum_{i,j} bK_i(s, t) \cdot K_j(s^-_a, t^-_a), \quad 1 \leq i, \ 1 \leq j, \ i + j < b_{a_{\text{max}}}
\end{align*}
\]

Figure 3: Computation of relation kernel.

Adaptation of a Least Squares SVM [Suykens et al. 2002] to a MIL setting: Weighted Least Squares SVM (WLS-SVM)

[De Belder, De Smet, Mochales & Moens SIM 2009]
WLS-SVM: errors in positive and negative bags are weighted differently to comply with MIL setting

Minimize over \( w, b \) and \( e \):

\[
J(w, b, e) = \frac{1}{2} \|w\|^2 + \frac{C}{L} (v_p \Xi_p + \xi)
\]

\[
\Xi_p = \sum_{B_i \in B^+} \sum_{x \in B_i} e_x^2
\]

\[
\Xi_n = \sum_{B_i \in B^-} \sum_{x \in B_i} e_x^2
\]

\[
v_p = \frac{1}{\gamma c_p}
\]

\[
v_n = \frac{1}{\gamma c_n}
\]

Subject to constraints:

\[
w \phi(x) + b = +1 - e_x, \quad \forall x \in B_i \in B^+,
\]

\[
w \phi(x) + b = -1 + e_x, \quad \forall x \in B_i \in B^-,
\]
Results “Acquisition” relation

<table>
<thead>
<tr>
<th></th>
<th>SSK</th>
<th>BOW</th>
<th>SSK-T1</th>
<th>BOW-T2</th>
<th>SSK-T2</th>
</tr>
</thead>
<tbody>
<tr>
<td>WLS:</td>
<td>80,41</td>
<td>33,46</td>
<td>85,80</td>
<td>55,08</td>
<td><strong>87,08</strong></td>
</tr>
<tr>
<td>QP:</td>
<td>77,62</td>
<td>25,50</td>
<td>83,93</td>
<td>44,77</td>
<td><strong>86,09</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
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<th></th>
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<th>BOW-T2</th>
<th>SSK-T2</th>
</tr>
</thead>
<tbody>
<tr>
<td>WLS:</td>
<td>52,00</td>
<td>22,90</td>
<td>71,00</td>
<td>39,56</td>
<td><strong>86,28</strong></td>
</tr>
<tr>
<td>QP:</td>
<td>51,18</td>
<td>23,63</td>
<td>67,16</td>
<td>30,84</td>
<td>62,65</td>
</tr>
</tbody>
</table>

Own dataset
Dataset Raymond Mooney

Results “Born in” relation

<table>
<thead>
<tr>
<th></th>
<th>SSK</th>
<th>BOW</th>
<th>SSK-T1</th>
<th>BOW-T2</th>
<th>SSK-T2</th>
</tr>
</thead>
<tbody>
<tr>
<td>WLS:</td>
<td>84,90</td>
<td>17,54</td>
<td>95,08</td>
<td>52,30</td>
<td><strong>94,95</strong></td>
</tr>
<tr>
<td>QP:</td>
<td>88,51</td>
<td>52,61</td>
<td>94,00</td>
<td>77,96</td>
<td><strong>96,07</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>SSK</th>
<th>BOW</th>
<th>SSK-T1</th>
<th>BOW-T2</th>
<th>SSK-T2</th>
</tr>
</thead>
<tbody>
<tr>
<td>WLS:</td>
<td>68,07</td>
<td>8,76</td>
<td>87,54</td>
<td>18,92</td>
<td><strong>89,38</strong></td>
</tr>
<tr>
<td>QP:</td>
<td>84,77</td>
<td>18,69</td>
<td>88,40</td>
<td>20,00</td>
<td><strong>90,02</strong></td>
</tr>
</tbody>
</table>
3. A classifier is trained from labeled and unlabelled examples

= **Semi-supervised learning**: most known forms are:

- Self-learning: iterative retraining after labeling of data points for which the current model is most confident
- Transductive inference: no general decision rule is inferred, only the labels of the unannotated examples are predicted according to a most likely model
Fig. 6.3. Self-training: A classifier is incrementally trained (blue line), first based on the labeled seeds, and then based on the labeled seeds and a set of unlabeled examples that are labeled with the current classifier. The dotted blue line represents the set of all unlabeled examples that were considered for labeling in this step.
Benefit of semi-supervised learning

But does this hold for all types of text classification?

Figure 2: Schematic figure illustrating how unlabeled data might improve a supervised classifier. Grey dots are unlabeled data, white dots labeled data and the dotted line the classification boundary.
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Text categorization

- Good results:
  - Generative model: e.g., self learning with Naive Bayes and Expectation Maximization, e.g., ca. average 95% accuracy on standard Reuters text categories, but use of multiple mixture components per class [Nigam, McCallum & Mitchell SL 2006]
  - Discriminative model: transductive learning with SVM e.g., better results when few training data, approach results SVM with more training data (accuracy > 80 %) [Joachims SL 2006]
Semi-supervised smoothness assumption: if two points in a high density region are close, so should be the corresponding classes.

Cluster assumption: the points of each class tend to form a cluster.

=> These assumptions do not necessarily hold for fine-grained text classification tasks!

Manifold assumption: curse of dimensionality: many features → many training examples.

[Chapelle, Schölkopf & Zien SL 2006]
When does semi-supervised learning work?

- For semi-supervised learning to work: it is an important prerequisite that the distribution of examples, which the unlabeled examples help elucidate, is relevant for the classification problem [Chapelle, Schölkopf & Zien SL 2006]

- Model learned from the labeled examples should be rather correct [Cozman & Cohen SL 2006]

- => evidenced by own research for semantic role labeling [Deschacht & Moens Technical report 2009]
4. We use few examples for training, but use additional constraints

- Knowledge of language or cognitive knowledge on how people understand text might help:
  - For selecting seed labeled examples
  - For adding additional constraints
- Illustrated with the recognition of temporal information in text
Recognition of temporal relations

- Between an event and time expressions that occur within the same sentence
- Between document creation time and an event
- Between the main events of adjacent sentences

⇒ Markov Logic model that jointly identifies these relations:
  ⇒ Explicit incorporation of (soft) temporal constraints

[Yoshikawa, Riedel, Asahura & Matsumoto ACL 2009]
Constraints help in **resolving ambiguity**: [Yoshikawa et al. 2009] reported 2% rise in accuracy compared to state of the art (average accuracy over above tasks = 68.9%)

=> But still problem of the variety of patterns in language
5. We use few examples for training, but perform a constrained expansion

Illustrated with semantic role labeling:

**fall.01**
Arg1: Logical subject, patient, thing falling
Arg2: Extent, amount fallen
Arg3: Start point
Arg4: End point, end state of Arg1
Ex1: [Arg1 Sales] *fell* [Arg4 to $251.2 million] [Arg3 from $278.7 million].
Ex2: [Arg1 The average junk bond] *fell* [Arg2 by 3.7%].
Latent Words Language Model

- Generative model of natural language
- Latent variable (hidden word) models *words* that have a *similar meaning* in a *specific* left and right *context*

[Deschacht & Moens EMNLP 2009]
Latent Words Language Model

- Model is trained on large corpus:
  - Initialization with trigram language model and Kneser-Ney smoothing
  - Updated with Gibbs sampling

\[ P^\tau(h_j|w_j, h_{0}^{j-1}, h_{j+1}^{Z}) = \frac{P^\tau(w_j|h_j)P^\tau(h_j|h_{j-2}^{j-1}h_{j+1}^{j+2})}{\sum_{h_i} P^\tau(w_i|h_i)P^\tau(h_j|h_{j-2}^{j-1}h_{j+1}^{j+2})} \]

- Context-dependent distribution of hidden words can be inferred for a new text
Latent Words Language Model

Perplexity on unseen text
(when converted to sequential tri-gram model):

<table>
<thead>
<tr>
<th>Model</th>
<th>Reuters</th>
<th>APNews</th>
<th>EnWiki</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kneser-Ney LM</td>
<td>113.15</td>
<td>132.99</td>
<td>160.83</td>
</tr>
<tr>
<td>Class based LM</td>
<td>108.38</td>
<td>125.65</td>
<td>149.21</td>
</tr>
<tr>
<td>LWLM</td>
<td><strong>99.12</strong></td>
<td><strong>116.65</strong></td>
<td><strong>148.12</strong></td>
</tr>
</tbody>
</table>

=> Outperforms other current language models for predicting the English language

[Deschacht & Moens Benelearn 2009]
Examples on unseen texts

<table>
<thead>
<tr>
<th>Compuserve corp</th>
<th>said</th>
<th>Tuesday</th>
<th>it anticipates a loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microsoft inc</td>
<td>told</td>
<td>Friday</td>
<td>they</td>
</tr>
<tr>
<td>Chrysler corp.</td>
<td>told</td>
<td>Friday</td>
<td>expected</td>
</tr>
<tr>
<td>Oracle ltd</td>
<td>added</td>
<td>Thursday</td>
<td></td>
</tr>
<tr>
<td>Software co</td>
<td>say</td>
<td>Wednesday</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>A the Japanese electronics executive was kidnapped in Mexico</th>
</tr>
</thead>
<tbody>
<tr>
<td>the u.s. tobacco director is abducted on usa</td>
</tr>
<tr>
<td>its german sales manager we killed at uk</td>
</tr>
<tr>
<td>an brish consulting economist are found of australia</td>
</tr>
<tr>
<td>one russian electric spokesman be abduction into canada</td>
</tr>
</tbody>
</table>
Latent words for SRL

- Latent words are used as probabilistic features in MEMM for classification (results as F$_1$ - CoNLL dataset):

<table>
<thead>
<tr>
<th>Amount of training data</th>
<th>5%</th>
<th>20%</th>
<th>50%</th>
<th>100%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard SRL</td>
<td>40.49%</td>
<td>67.23%</td>
<td>74.93%</td>
<td>78.65%</td>
</tr>
<tr>
<td>SRL + LW</td>
<td>60.29%</td>
<td>72.88%</td>
<td>76.42%</td>
<td>80.98%</td>
</tr>
</tbody>
</table>

- Word expansion improves recall
- Word sense disambiguation improves precision
- Easy to use in many other NLP applications

[Deschacht & Moens EMNLP 2009]
6. Cross-modal processing

- Unsupervised alignment of names and faces in “Labeled faces in the wild” dataset: from Yahoo!news
  [Pham, Moens & Tuytelaars IEEE Trans. Multimedia in press]
Vice President Dick Cheney speaks at a luncheon for Republican U.S. Senate candidate John Cornyn Friday, July 19, 2002, in Houston. (AP Photo/Pat Sullivan)

President-elect Barack Obama is inching closer to naming former rival Sen. Hillary Clinton as his secretary of state, ABC News has learned. (Getty Images)

Danish director Lars Von Trier (C), Australian actress Nicole Kidman and Swedish actor Stellan Skarsgard (L) pose on a terrace of the Palais des festivals. (AFP/Boris Horvat)
Cross-modal processing

- Adaptation to alignment in *video* data

Time warping to align scripts and subtitles

*Dawn* returns with a spoon, wearing an innocent expression.
*Buffy* turns away to get another bowl.
Willow hugs Buffy.

Recognition of **event signaling verbs, nouns** though analysis of the video?

[CIAM IJCAI-09 workshop]
Conclusions

- Learning with a **minimum of supervision** when semantic labeling of text: very useful
- But, **understudied problem**
  - Active learning
  - Model building for semi-supervised learning
  - Frequent phenomena allow already extracting semantic knowledge: large data sets on the Web help!
  - Better knowledge on the distributions of language patterns in context will help: already shown with LWLM
  - Multimodal processing: AI again becoming a more integrated discipline?


