# Question Classification (cont'd)

Ling573
NLP Systems & Applications
April 12, 2011

# Upcoming Events

- Two seminars: Friday 3:30
  - Linguistics seminar:
    - Janet Pierrehumbert: Northwestern
      - **Example-Based Learning and the Dynamics of the Lexicon**
  - AI Seminar:
    - Patrick Pantel: MSR
      - **Associating Web Queries with Strongly-Typed Entities**

# Roadmap

- Question classification variations:
  - SVM classifiers
  - Sequence classifiers
  - Sense information improvements
- Question series

# Question Classification with Support Vector Machines

- Hacioglu & Ward 2003
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  - POS, chunk info; NE tagging; other sense info
- Preprocessing:
  - Only letters, convert to lower case, stopped, stemmed
- Terms:
  - Most informative 2000 word N-grams
  - Identifinder NE tags (7 or 9 tags)

# Classification & Results

- Employs support vector machines for classification
  - Best results: Bi-gram, 7 NE classes

| Method | 1-gram | 2-gram | 3-gram |
|---|---|---|---|
| No NE | 79.4% | 80.2% (77.8%) | 78.4% |
| NE-7 | 81.4% | <u>82.0%</u> ( 81.2%) | 80.2% |
| NE-29 | 75.4 | 78.6% ( 79.2%) | 78.8% |

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    - How much does a rhino weigh?
  - Single contiguous span of tokens
    - How much does a rhino weigh?
    - *Who* is the **CEO** of IBM?

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# Effect of Informer Spans

- Classifier: Linear SVM + multiclass

| Features | Coarse | Fine |
|---|---|---|
| Question trigrams | 91.2 | 77.6 |
| All question *q*grams | 87.2 | 71.8 |
| All question unigrams | 88.4 | 78.2 |
| **Question bigrams** | 91.6 | 79.4 |
| +informer q-grams | 94.0 | 82.4 |
| +informer hypernyms | **94.2** | **88.0** |
| Question unigrams + all informer | 93.4 | 88.0 |
| Only informer | 92.2 | 85.0 |
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# Perfect vs CRF Informer Spans

| | | B | Only Informers | | | B+ | B+ | B+ |
|---|---|---|---|---|---|---|---|---|
| Type | #Quest. | (Bigrams) | Perf.Inf | H.Inf | CRF.Inf | Perf.Inf | H.Inf | CRF.Inf |
| what | 349 | **88.8** | 89.4 | 69.6 | 79.3 | **91.7** | 87.4 | 91.4 |
| which | 11 | **72.7** | 100.0 | 45.4 | 81.8 | **100.0** | 63.6 | 81.8 |
| when | 28 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| where | 27 | 100.0 | 96.3 | 100.0 | 96.3 | 100.0 | 100.0 | 100.0 |
| who | 47 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| how_* | 32 | 100.0 | 96.9 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| rest | 6 | 100.0 | 100.0 | 100.0 | 66.7 | 100.0 | 66.7 | 66.7 |
| Total | 500 | 91.6 | 92.2 | *77.2* | 84.6 | 94.2 | *90.0* | 93.4 |
| **50 fine classes** | | | | | | | | |
| what | 349 | **73.6** | 82.2 | 61.9 | 78.0 | **85.1** | 79.1 | 83.1 |
| which | 11 | **81.8** | 90.9 | 45.4 | 73.1 | **90.9** | 54.5 | 81.8 |
| when | 28 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| where | 27 | 92.6 | 85.2 | 92.6 | 88.9 | 88.9 | 92.5 | 88.9 |
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| rest | 6 | 66.7 | 66.7 | 66.7 | 66.7 | 100.0 | 66.7 | 66.7 |
| Total | 500 | 79.4 | 85.0 | *69.6* | 78.0 | 88.0 | *82.6* | 86.2 |

# Recognizing Informer Spans

- Idea: contiguous spans, syntactically governed

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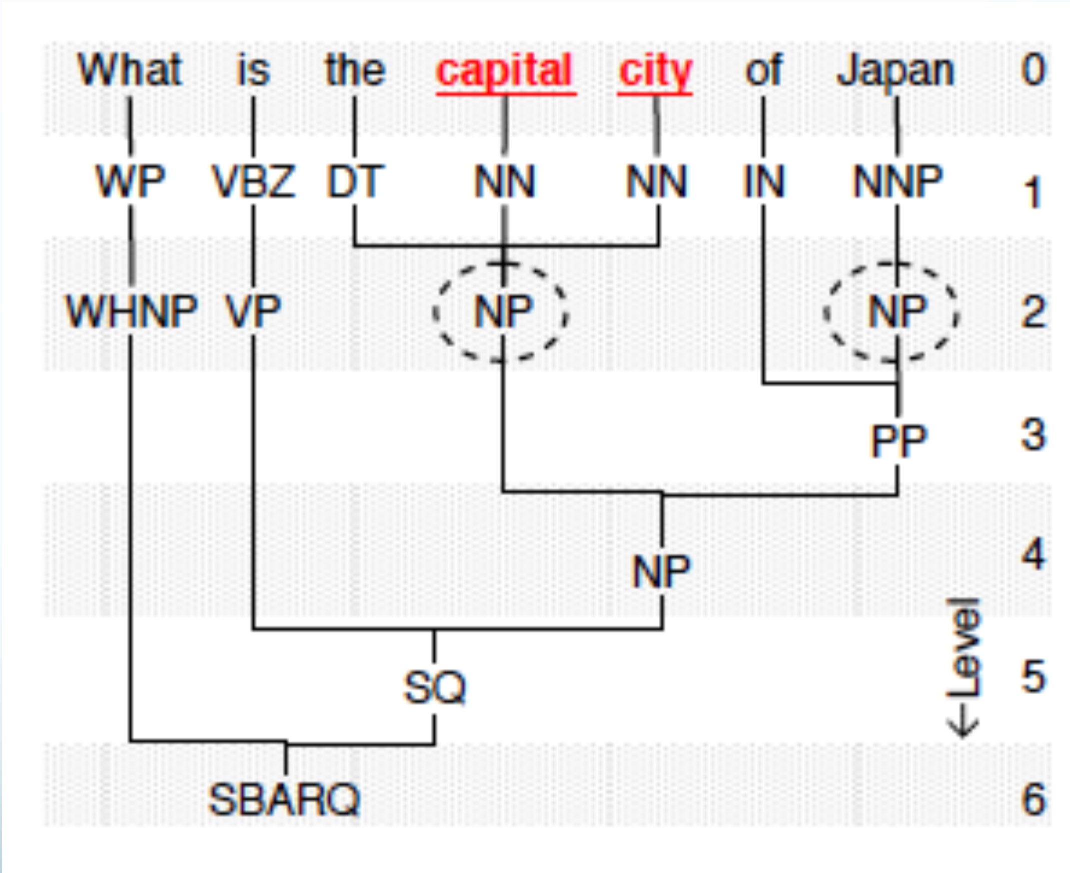
- Matrix of features derived from parse tree
  - Cell:x[i,l], i is position, l is depth in parse tree, only 2
  - Values:
    - Tag: POS, constituent label in the position
    - Num: number of preceding chunks with same tag

# Parser Output

- Parse



# Parse Tabulation

- Encoding and table:

| $i$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| $y_i$ | 0 | 0 | 0 | 1 | 1 | 2 | 2 |
| $x_i$ | What | is | the | capital | city | of | Japan |
| $\ell \downarrow$ | Features for $x_i$s | | | | | | |
| 1 | WP,1 | VBZ,1 | DT,1 | NN,1 | NN,1 | IN,1 | NNP,1 |
| 2 | WHNP,1 | VP,1 | NP,1 | NP,1 | NP,1 | Null,1 | NP,2 |
| 3 | Null,1 | Null,1 | Null,1 | Null,1 | Null,1 | PP,1 | PP,1 |
| 4 | Null,1 | Null,1 | NP,1 | NP,1 | NP,1 | NP,1 | NP,1 |
| 5 | Null,1 | SQ,1 | SQ,1 | SQ,1 | SQ,1 | SQ,1 | SQ,1 |
| 6 | SBARQ | SBARQ | SBARQ | SBARQ | SBARQ | SBARQ | SBARQ |

# CRF Indicator Features

- Cell:
  - IsTag, IsNum: e.g. $y_4 = 1$ and x[4,2].tag=NP
  - Also, IsPrevTag, IsNextTag

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| | |
|---|---|
| IsTag | 0.368 |
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- Question accuracy: Oracle: 88%; CRF: 86.2%

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    - Employ WSD techniques
  - SVM, MaxEnt classifiers

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  - Also, simple regexp for other feature type
    - E.g. 'what is' cue to definition type

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  - How deep?
    - Based on validation set: 6
- Q Type similarity: compute similarity b/t headword & type
  - Use type as feature

# Other Features

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- Question wh-word:
  - What,which,who,where,when,how,why, and rest
- N-grams: uni-,bi-,tri-grams
- Word shape:
  - Case features: all upper, all lower, mixed, all digit, other

# Results

| | | 6 class | | 50 class | |
|---|---|---|---|---|---|
| | | SVM | ME | SVM | ME |
| wh-word + head word | | 92.0 | 92.2 | 81.4 | 82.0 |
| wh-word + | depth=1 | 92.0 | 91.8 | 84.6 | 84.8 |
| head word + | depth = 3 | 92.0 | 92.2 | 85.4 | 85.4 |
| direct hypernym | depth = 6 | 92.6 | 91.8 | 85.4 | 85.6 |
| wh-word + head + indirect hypernym | | 91.8 | 92.0 | 83.2 | 83.6 |
| unigram | | 88.0 | 86.6 | 80.4 | 78.8 |
| bigram | | 85.6 | 86.4 | 73.8 | 75.2 |
| trigram | | 68.0 | 57.4 | 39.0 | 44.2 |
| word shape | | 18.8 | 18.8 | 10.4 | 10.4 |

Per feature-type results:

# Results: Incremental

- Additive improvement:

6 coarse classes

| Type | #Quest | wh+headword | | +headword hypernym | | +unigram | | +word shape | |
|---|---|---|---|---|---|---|---|---|---|
| | | SVM | ME | SVM | ME | SVM | ME | SVM | ME |
| what | 349 | 88.8 | 89.1 | 89.7 | 88.5 | 89.7 | 90.3 | 90.5 | 91.1 |
| which | 11 | 90.9 | 90.9 | 100 | 100 | 100 | 100 | 100 | 100 |
| when | 26 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| where | 27 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| who | 47 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| how | 34 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| why | 4 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| rest | 2 | 100 | 100 | 50.0 | 50.0 | 100 | 50.0 | 100 | 50.0 |
| total | 500 | 92.0 | 92.2 | 92.6 | 91.8 | 92.8 | 93.0 | 93.4 | 93.6 |

50 fine classes

| Type | #Quest | wh+headword | | +headword hypernym | | +unigram | | +word shape | |
|---|---|---|---|---|---|---|---|---|---|
| | | SVM | ME | SVM | ME | SVM | ME | SVM | ME |
| what | 349 | 77.4 | 77.9 | 82.8 | 82.5 | 85.4 | 85.1 | 86.2 | 86.0 |
| which | 11 | 81.8 | 90.9 | 81.8 | 90.9 | 90.9 | 100 | 90.9 | 100 |
| when | 26 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| where | 27 | 92.6 | 92.6 | 92.6 | 92.6 | 92.6 | 92.6 | 92.6 | 92.6 |
| who | 47 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| how | 34 | 76.5 | 76.5 | 76.5 | 79.4 | 97.1 | 91.2 | 97.1 | 91.2 |
| why | 4 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| rest | 2 | 0.0 | 0.0 | 50.0 | 50.0 | 0.0 | 50.0 | 0.0 | 50.0 |
| total | 500 | 81.4 | 82.0 | 85.4 | 85.6 | 88.6 | 88.4 | 89.2 | 89.0 |

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| Target 27 - *Jennifer Capriati* | |
|---|---|
| Q27.2 | Who is her coach? |
| Q27.3 | Where does she live? |

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