

# Plan for the Talk

- Subjectivity and sentiment in language
- Opinion extraction
  - definition and examples
- Algorithms and evaluation
- Demo

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# Subjective Language

- Subjective sentences express private states, i.e. internal mental or emotional states
  - speculations, beliefs, emotions, evaluations, goals, opinions, judgments, ...
    - Jill said, "I hate Bill."
    - John *thought* about whom to vote for.
    - Claire *hoped* her lecture would go well.

# Subjectivity vs. Sentiment

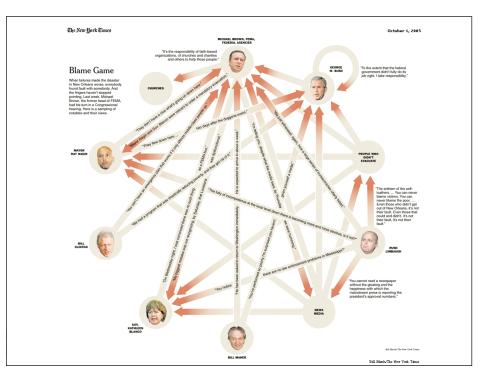
- Sentiment expressions are a type of subjective expression
  - expressions of *positive* and *negative* emotions, judgments, evaluation<u>s</u>, ...
    - Jill said, "I *hate* Bill."
    - John *thought* about whom to vote for.
    - Claire *hoped* her lecture would go well.

In this talk, opinion = any subjective language

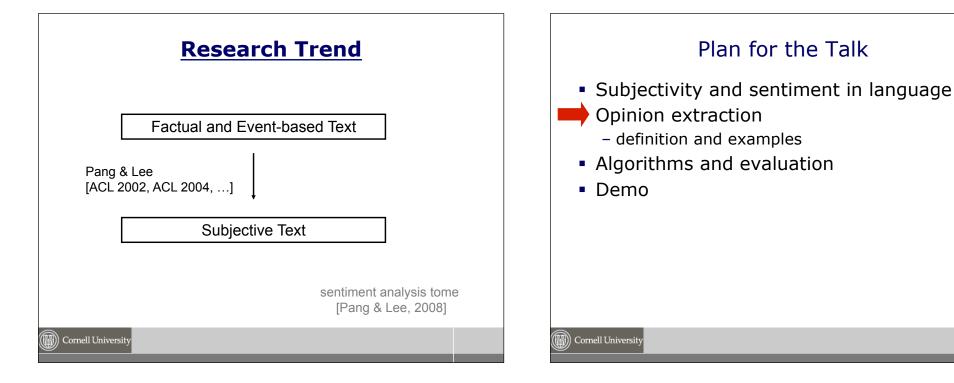
# Why Study Opinions?

- Web Queries of a Subjective Nature
  - How have **business** views towards **global** climate change varied over the past decade?
  - What is the reaction in Asia to the to the Bush policy towards the Kyoto Protocol?
  - How have **consumers and businesses** responded to Gore's "An Inconvenient Truth"?
  - Who were the first people to propose **bailout** options for banks in the current economic crisis?
  - What does **Sarah Palin** think about **<X>**?

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Plan for the Talk



### Fine-grained Opinion Extraction

...The Australian press has launched a bitter attack on Italy after seeing their beloved Socceroos eliminated on a controversial late penalty. Italian coach Lippi has been blasted for his comments after the game.

In the opposite camp, Lippi is preparing his side for the upcoming game with Ukraine. He hailed 10-man Italy's determination to beat Australia and said their winning penalty was rightly given.

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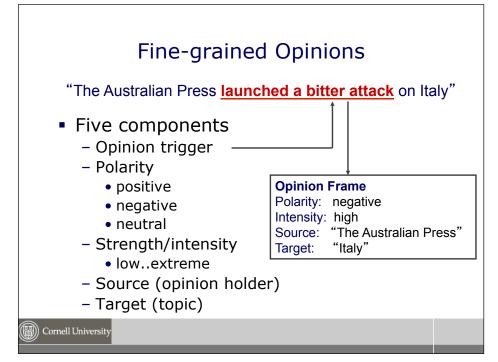
...

#### Fine-grained Opinion Extraction

Australian press has <u>launched a bitter attack</u> on Italy after seeing their <u>beloved</u> Socceroos eliminated on a <u>controversial</u> late penalty. Italian coach Lippi has also been <u>blasted</u> for his comments after the game.

In the opposite camp Lippi is preparing his side for the upcoming game with Ukraine. He <u>hailed</u> 10man Italy's <u>determination</u> to beat Australia and said the penalty was <u>rightly given</u>.

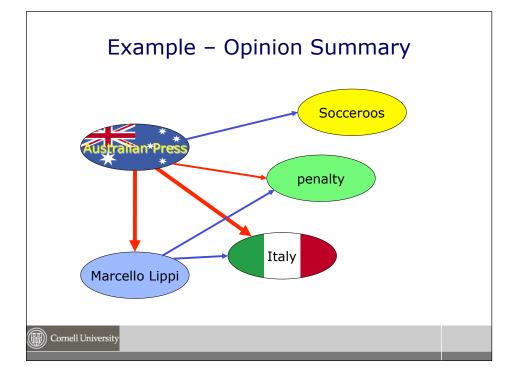
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#### Example – fine-grained opinions

Australian press has <u>launched a bitter attack</u> on Italy after seeing their <u>beloved</u> Socceroos eliminated on a <u>controversial</u> late penalty. Italian coach Lippi has also been <u>blasted</u> for his comments after the game.

In the opposite camp Lippi is preparing his side for the upcoming game with Ukraine. He <u>hailed</u> 10man Italy's <u>determination</u> to beat Australia and said the penalty was <u>rightly given</u>.



# What makes this hard?

- MPQA corpus
  - 2812 opinion expressions (medium or higher intensity)
  - 4282 content word tokens
  - 49% are unique
- For words in these expressions that appear > 1 time
  - 38% appear in *both* subjective and objective contexts
    - achieved (2 subjective, 4 objective);
    - against (15 subjective, 40 objective);
    - considering (3 subjective, 7 objective);
    - difficult (7 subjective, 8 objective);
    - fact (14 subjective, 7 objective);

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[Wiebe, Wilson, Cardie 2004]

# What makes this hard?

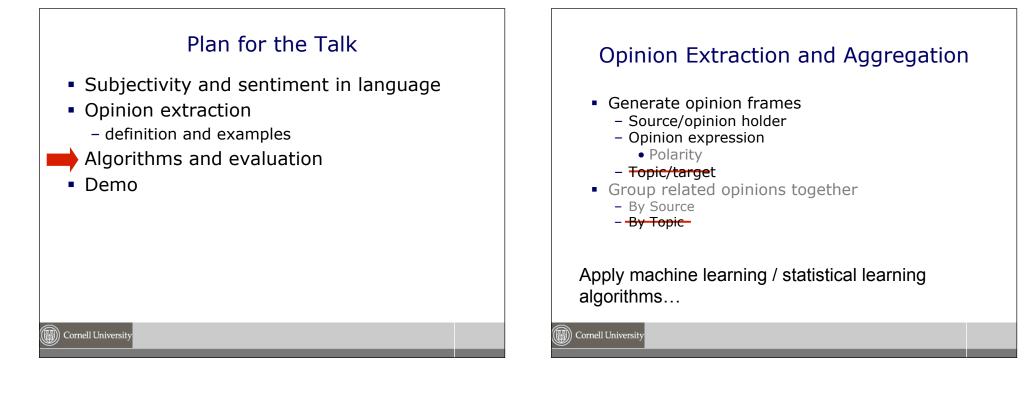
- MPQA corpus (dev set)
  - 41.5% of sentences are objective
  - 44.0% of sentences contain mixtures of opinions and objective speech events
    - Half of these contain 3 or more
  - Differing polarities for opinion expressions from the same sentence

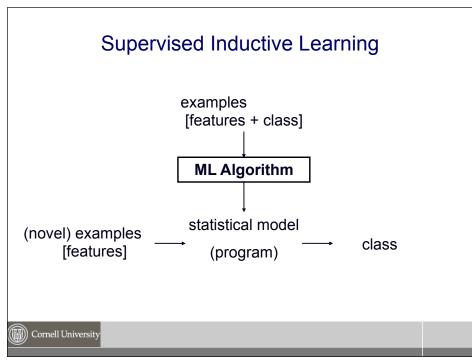
	positive	negative	neutral	both
positive	36	32	44	2
negative	66	32	66	7
neutral	55	69	135	4
both	2	2	7	0

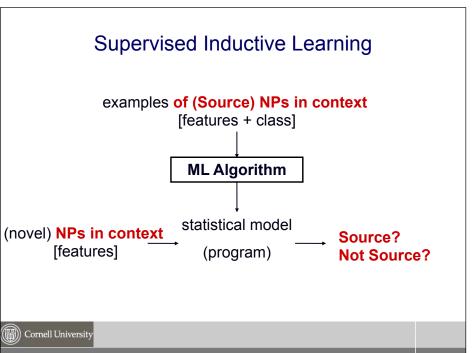
Thanks, Ainur!

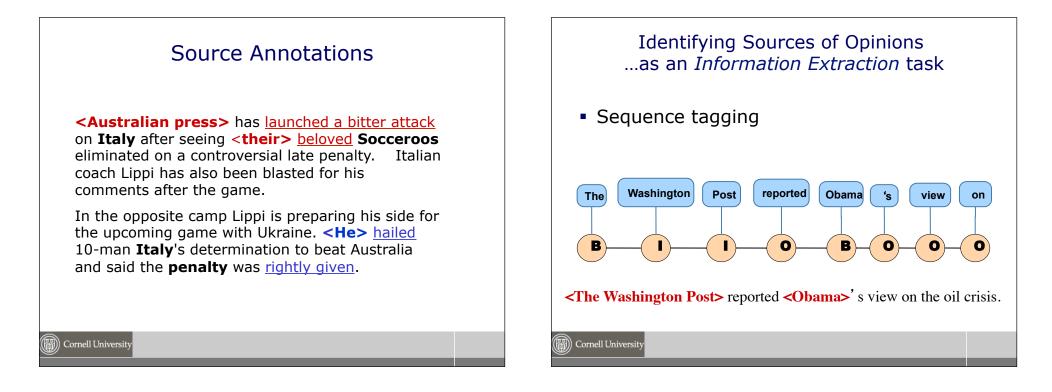
Not so easy for people either...

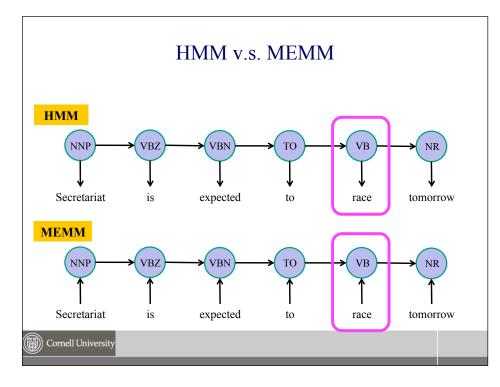


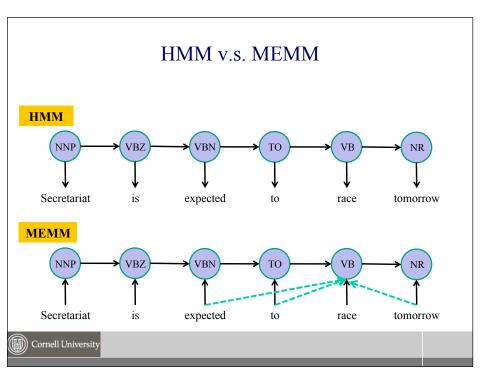


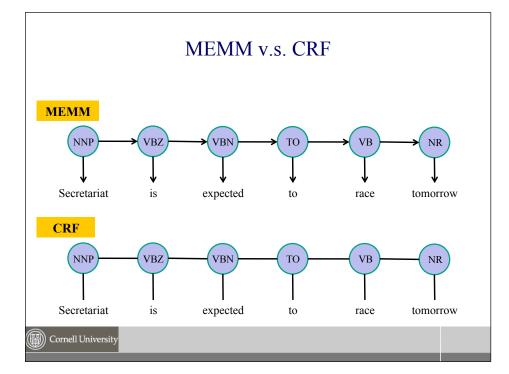


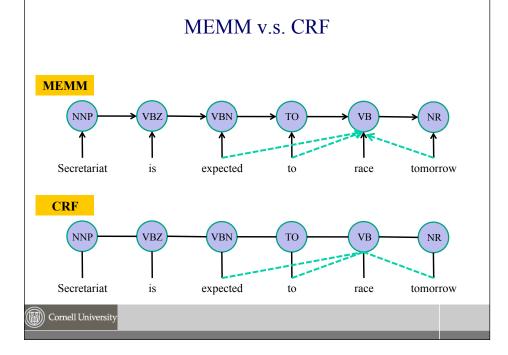






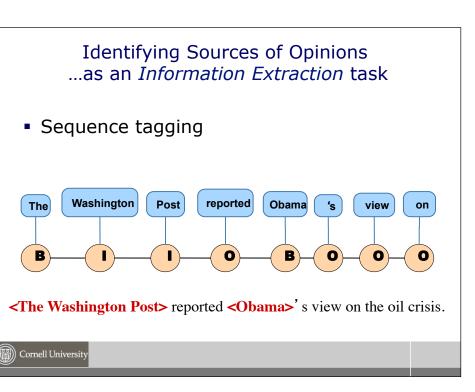






# Conditional Random Fields

- Discriminative training
- Incorporation of arbitrary nonindependent features (past + future)
  - semantic class, suffixes, constituent type, etc.
- Perform better than related classification and generative models (e.g. HMMs)
  - Part-of-speech tagging [Lafferty et al., 2001]
  - Noun phrase chunking [Sha and Pereira, 2003]
  - Human protein name tagging [Bunescu et al. 2004]



# Features for Source Extraction Syntactically... mostly noun phrases Semantically... entities that can bear opinions Functionally... linked to opinion expressions

#### Features for Source Extraction

- Words [-4,+4]
- Capitalization
- Part-of-speech tags [-2,+2]
- Opinion phrase lexicon
  - Derived from training data
  - Wiebe et al.'s [2002] 500+ word lexicon
- Shallow semantic class information
  - Sundance partial parser and named entity tagger
  - WordNet hypernym
- Constituent type
- Grammatical role
  - Collins' parser
- Task-specific combinations
  - E.g., Parent contains opinion word

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# Evaluation

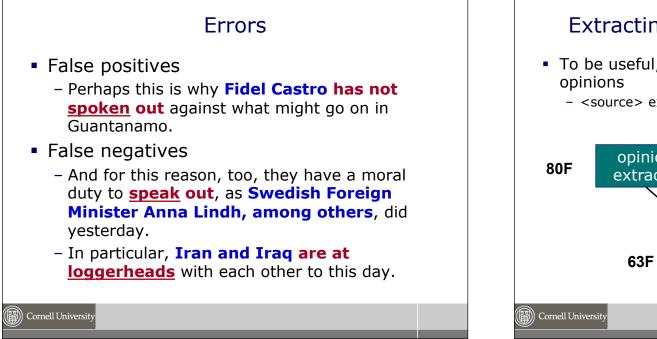
- MPQA data set (www.cs.pitt.edu/mpqa)
  - ~550 documents
  - Manually annotated w.r.t. fine-grained opinion information
  - Provides gold standard
- Automatically derive training/test examples
- 10-fold cross-validation
- Evaluation measures
  - Precision
  - Recall
  - F-measure

# **Results: Opinion Holders**

- >82% precision (accuracy)
- ~60% recall (coverage)
- 69.4 F-measure

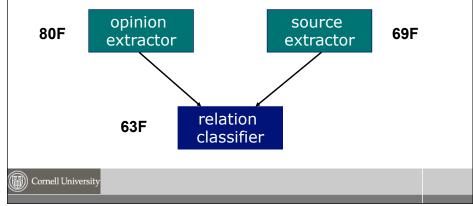
So there's a lot of room for improvement...

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# Extracting and Linking to Opinions

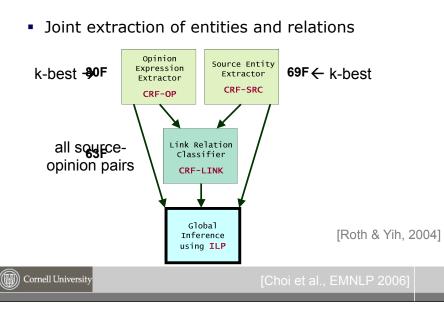
- To be useful, we need to link sources to their opinions
  - <source> expresses <opinion>



# **Research Trend**: Structured Learning

- Beyond simple classification tasks
- Dependent/output variable has an internal structure
- Multiple dependent/output variables with dependencies or constraints among them
- E.g. syntactic parse tree, source-expressesopinion relation

#### Opinion Frame Extraction via CRFs and ILP



## Constraints

- Binary integer variables O\_i, S\_j, L\_i,j
   Weights for O\_i, S\_j, L\_i,j are based on probabilities from individual classifiers
- Constraints

 $\begin{aligned} &\forall i, \ O_i = \sum_j L_{i,j} &: \text{link coherency(only one link from each opinion)} \\ &\forall j, \ S_j + A_j = \sum_i L_{i,j} &: \text{link coherency(upto two links from each source)} \\ &\forall j, \ A_j - S_j \leq 0 &: \text{link coherency(preferably one link from each source)} \\ &\forall i, j, i < j, \ X_i + X_j = 1, \ X \in \{S, O\} \end{aligned}$ 

: entity coherency(for all pairs of entities with overlapping spans)

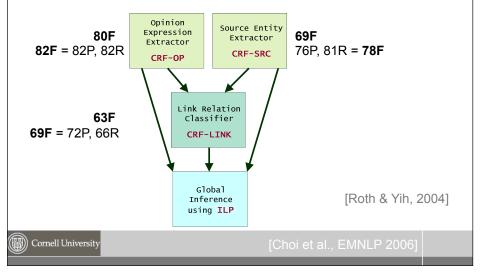
Objective function

$$f = \sum_{i} (\mathbf{w}_{O_i} O_i) + \sum_{i} (\overline{\mathbf{w}}_{O_i} \overline{O}_i) + \sum_{j} (\mathbf{w}_{S_j} S_j) + \sum_{j} (\overline{\mathbf{w}}_{S_j} \overline{S}_j) + \sum_{i,j} (\mathbf{w}_{L_{i,j}} L_{i,j}) + \sum_{l,j} (\overline{\mathbf{w}}_{L_{i,j}} \overline{L}_{i,j})$$

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#### Opinion Frame Extraction via CRFs and ILP

Joint extraction of entities and relations



# Update on Results

- Extracting Opinion Expressions with semi-Markov Conditional Random Fields (Yang & Cardie, EMNLP 2012)
  - Handles indirect (as well as direct) opinion expressions
    - The International Committee of the Red Cross, [as usual]<sub>[ESE]</sub>, [has refused to make any statements]
       [DSE].
    - The Chief Minister [said]<sub>[DSE]</sub> that [the demon they have reared will eat up their own vitals]<sub>[ESE]</sub>.
- Joint Inference for Fine-Grained Opinion Analysis (Yang & Cardie, submitted)
  - Handles source + target entities
  - Handles is-from + is-about relations
  - Handles cases with implicit sources

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# Appinions Demo

- Opinion frames
  - Opinion expressions
  - Opinion holder
  - Polarity
  - Topic
- Aggregation
  - w.r.t. opinion holder or topic
  - over time
- Use to derive social networks
  - Determine key influencers for particular topics