# Information Extraction from the World Wide Web

**CSE 454** 

Based on Slides by

William W. Cohen

Carnegie Mellon University

Andrew McCallum

University of Massachusetts Amherst

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## **Quick Review**

## **Bayes Theorem**



$$P(H \mid E) = \frac{P(E \mid H)P(H)}{P(E)}$$

## **Bayesian Categorization**

- Let set of categories be  $\{c_1, c_2, ... c_n\}$
- Let E be description of an instance.
- Determine category of E by determining for each  $c_i$

$$P(c_i \mid E) = \frac{P(c_i)P(E \mid c_i)}{P(E)}$$

• P(E) can be determined since categories are complete and disjoint.

$$\sum_{i=1}^{n} P(c_i \mid E) = \sum_{i=1}^{n} \frac{P(c_i)P(E \mid c_i)}{P(E)} = 1$$

$$P(E) = \sum_{i=1}^{n} P(c_i) P(E \mid c_i)$$

## Naïve Bayesian Motivation

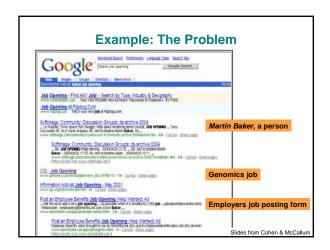
- Problem: Too many possible instances (exponential in m) to estimate all P(E | c<sub>i</sub>)
- If we assume features of an instance are independent given the category (c) (conditionally independent).

$$P(E \mid c_i) = P(e_1 \land e_2 \land \dots \land e_m \mid c_i) = \prod_{j=1}^m P(e_j \mid c_i)$$

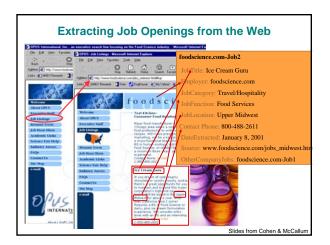
• Therefore, we then only need to know  $P(e_j | c_i)$  for each feature and category.

**Information Extraction** 

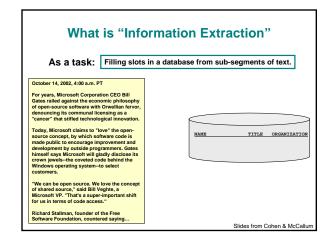
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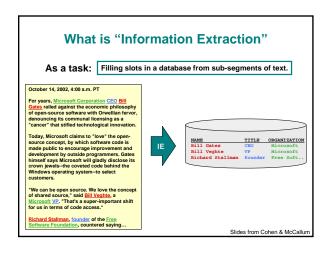


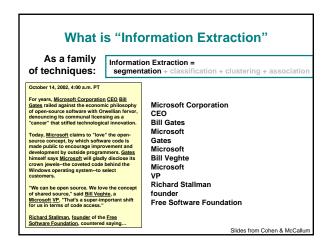


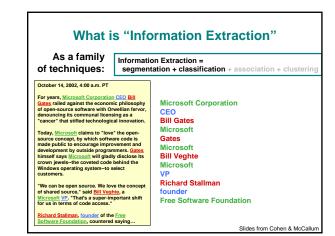


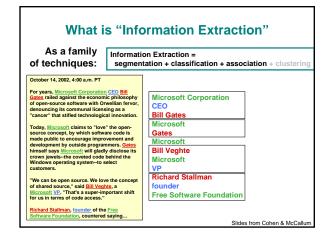


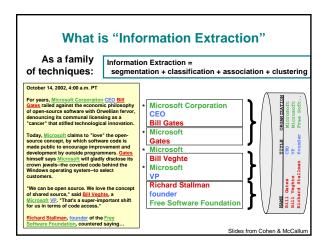








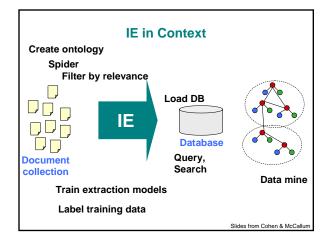




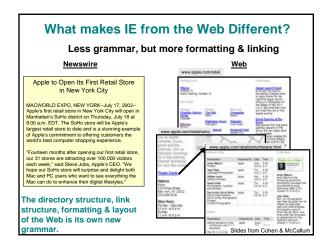
**IE History** 

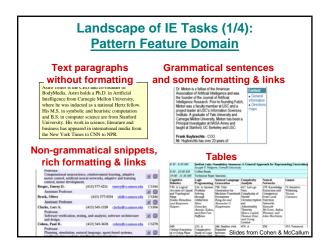
Pre-Web

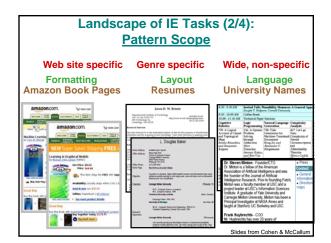
Web

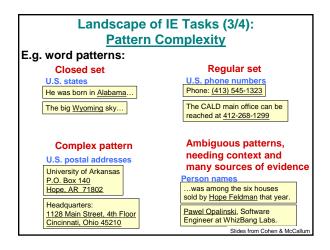


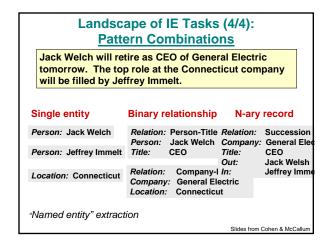
#### Mostly news articles De Jong's FRUMP [1982] Hand-built system to fill Schank-style "scripts" from news wire - Message Understanding Conference (MUC) DARPA ['87-'95], TIPSTER ['92-· Most early work dominated by hand-built models - E.g. SRI's FASTUS, hand-built FSMs. But by 1990's, some machine learning: Lehnert, Cardie, Grishman and then HMMs: Elkan [Leek '97], BBN [Bikel et al '98] AAAI '94 Spring Symposium on "Software Agents" Much discussion of ML applied to Web, Maes, Mitchell, Etzioni. Tom Mitchell's WebKB, '96 - Build KB's from the Web. Wrapper Induction - First by hand, then ML: [Doorenbos '96], [Soderland '96], [Kushmerick '97],... Slides from Cohen & McCallum

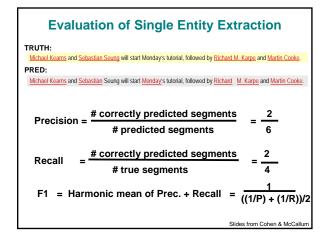








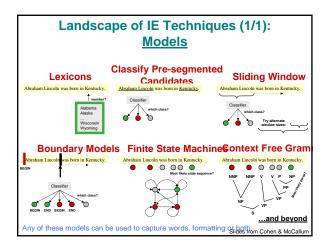




### State of the Art Performance

- · Named entity recognition
  - Person, Location, Organization, ...
  - F1 in high 80's or low- to mid-90's
- · Binary relation extraction
  - Contained-in (Location1, Location2) Member-of (Person1, Organization1)
  - F1 in 60's or 70's or 80's
- Wrapper induction
  - Extremely accurate performance obtainable
  - Human effort (~30min) required on each site

Slides from Cohen & McCallun



## Landscape: **Focus of this Tutorial** Pattern complexity closed set regular complex ambiguous Pattern feature domain words words + formatting formatting Pattern scope site-specific genre-specific general Pattern combinations entity binary n-ary lexicon regex window boundary FSM CFG Models Slides from Cohen & Mc

#### References

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