#### Computational Linguistics 1 CMSC/LING 723, LBSC 744



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# Agenda

HW7 due next Tuesday
Please provide a brief writeup of what you changed, and why you thought it would help. Include some examples where your changes improved the results, where it didn't, and report on the overall accuracy change as appropriate.
Also submit your code
Review for the final next Tuesday
Questions, comments, concerns?
Summarization
Information Extraction (IE)
Co-reference Resolution

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### Summarization

- Some key dimensions within which summarization systems differ
  - Extracting versus abstracting
- Single document versus multi-document
- · Query driven versus general summarization
- Summarization systems these days are most typically
  - Extractive: abstracting is very difficult
- Rarely, might see systems that 'fuse' sentences
  Multi-document: to exploit redundancy
- Introduces problems of co-reference, conflicting info
- · Query driven: summarization doesn't occur in a vacuum

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# **Extractive Summarization**

- Summary composed of extracted parts of documents
   Common granularity at sentence level, but not required
- In fact, get close to abstracting if unit is smaller
- Must first segment the document into extractable units
   Naive sentence segmentation: when you see a period, segment
- Then rank the extractable units
- Naive sentence ranking: position in document (earlier better)
  Then extract some number of the ranked extractable units
- Naive sentence selection: pick top *n* units

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# Sentence Selection

- Sentences can be similar across multiple documents
- The top of the list may include very similar sentences
- If we have limited space (say 250 words), repetition is not good
- Want to respect the ranking, yet penalize redundancy somehow
- · Integrating rank with penalty can be tricky

# Comparison to IR

- Both involve ranking according to some score; and selection
- Ranking criterion will differ . . .
- For IR, terms are weighted based on how they distinguish document(s) from others in the collection
- For summarization, want sentences that are "central" to the document(s)
- . . . but related: still care about term frequency, inverse document frequency and stop lists
- Pretty different use of vector space, however

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# Sentence-Ranking Possibilities

- Suppose we use TF\*IDF term weighting
- Create an n-dimensional normalized vector for document: d
- Create an n-dimensional normalized vector for each sentence: s
- · Rank sentences by:

$$\cos(d,s) = \sum_{i=1}^n d[i]s[i]$$

- Maybe other useful features?:
  - Position of sentence in the document
  - Distribution of terms across documents in the set
  - · Query terms (maybe by influencing term weighting?)

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# Query Expansion

- Relevant to both IR and summarization
- Given a query, expand to include related terms
- Can solve some issues from text normalization
  - query term: 'ncx1'; expand with: 'NCX1'
  - query term: 'regulation'; expand with 'regulating', 'regulate'
- Can also help by including semantically related words
   uery term: 'cow'; expand with 'bovine'
- Possible problem: swamping original terms with expanded terms

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### Summarization Evaluation

- This is a big, difficult topic: what makes a good summary
- Here we will focus on automatic evaluation given references
- Basic intuition, comparing two summaries, S<sub>1</sub> and S<sub>2</sub>
- To the extent that  $S_1$  overlaps more with a reference summary R, it is "better" than  $S_2$
- Key questions
- How does one measure overlap?
- · What about summary length?
- · What if there are multiple reference summaries?

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# ROUGE

- Measure overlap by counting matching *n*-grams
   n-gram is a word sequence of length *n*
- e.g., unigram 'dog'; bigram 'dog food'; trigram 'dog food can'
- Let c(x, s) be the count of n-gram x in summary s
- Let c(x, r) be the count of n-gram x in reference r
- For a given n, the ROUGE score is

$$ext{ROUGE-}n = rac{\sum_x \min\{c(x,r),c(x,s)\}}{\sum_x c(x,r)}$$

· Denominator reference count, thus a recall metric

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### Further topics of exploration

- Moving beyond TF\*IDF term weighting
- How can we find "central" sentences in new ways?Graph based random walk methods
- · Including multiple factors in sentence ranking
- Using the query to influence the term weighting
- Query expansion
- · Is there a principled way to reduce redundancy?

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#### Document Understanding Conference (DUC)

- Last few years focused on query-driven multi-doc summarization
- Has transitioned to "Text Analysis Conference" (TAC)
- New tasks of interest: update summaries; opinion summaries
- · Focus on multiple evaluation metrics
- Some manual, e.g., pyramid analysis
- Some automatic, e.g., ROUGE, BE
- · Lots of new ideas tried every year, mainly extractive techniques
- Data created through bakeoffs can be used for training systems

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- Information Extraction (IE) Co-reference Resolutior

# Information Extraction

#### IR versus IE

- · IR retrieves relevant documents from collections · Looking for documents or larger passages
- Using information theory, probabilistic theory, statistics
- IE extracts relevant information from documents
  - · Looking for structure
- · Using natural language processing

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# IE Tasks

- Most IE tasks involve:
- 1. Document segmentation
- 2. Labeling of segments
- 3. Discovery of relations between labeled segments
- Examples:

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- · Form filling from classified advertisements
- · Named entity recognition
- · Discovery of part/whole relations

# Example IE Task

From the 7th Message Understanding Conference (MUC-7)

- · Find the description of a launch event, and fill in:
  - Vehicle

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- Payload
- Mission Date
- Mission Site
- Mission Type (Military, Civilian)
- Mission Function (Test, Deploy, Retrieve)
- · Mission Status (Succeeded, Failed, In Progress, Scheduled) Other MUC tasks:
- · Latin American terrorism, Joint ventures, Microelectronics, Company management changes

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# IE as Tagging Tasks

- · Most segments in typical IE tasks are non-hierarchical and non-overlapping
- Thus can be modeled using simple finite-state models • For each label X, a word can begin (B-X) or be inside (I-X)
- · Some words may be outside (O) any labeled segment
- Ad hoc IR treats document as unordered set. .
- . . . but IE must take into account sequence information
  - · Previous word's tag may influence that of the current word
- · Typically include information about word sequence

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# Named Entity Recognition (NER): an IE Task

Begin segment words underlined and in red. Inside segment words just in red. Everything else outside segment.

Exchange activity in cardiomyocytes is regulated by several factors. It is activated by <u>cytosolic</u> Ca2+ and <u>MgATP</u> (20) and inhibited by <u>cytosolic</u> sodium (21) and <u>ATP</u> depletion (22). A high affinity <u>Ca2+-binding</u> domain has been identified in the large cytoplasmic loop (residues 371-508) that is believed to be responsible for calcium regulation (23). It is also inhibited by the exchanger inhibitory peptide, XIP, that corresponds to a 20-amino acid segment at  $\underline{the}\ N$ terminus of <u>the</u> large cytoplasmic loop (24).

### Co-reference Resolution: an IE Task

- Introduced as a task at MUC-6
- · Recognize referential relations among expressions
- Whole-part relations
- Set-subset
- Type-token
- Recognize identify of reference among (similar) noun
   phrases

# **Co-reference Examples**

- Names and aliases
   International Business Machines, IBM, Big Blue
   Mr. William H. Gates, Mr. Gates, Bill Gates
   Definite noun phrases
- the big computer company, the Armonk-based giant
  the head honcho at Microsoft, the world's richest man
- Pronouns

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• he, her, his, it, its, we, they, theirs, them, ours, your, ...

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# Another Co-reference Example

John went to Bill's car dealership to check out an Acura Integra. He looked at it for about an hour.

- · Possible interpretations:
  - · John looked at Bill's car dealership
- · Bill looked at John
- John looked at an Acura Integra
- John looked at Bill etc.
- Not just pronouns:

John went to Bill's car dealership to check out an Acura Integra. The car was just what he wanted.

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# **Co-reference Resolution**

- Two referring expressions that refer to the same referent are said to co-refer
- A referring expression is a natural language expression referring to an entity called the referent, e.g. the word Shaq and that guy dunking over there
- A referring expression *licensing* the use of another is known as the **antecedent**
- e.g. John went to ..., and he ...
- Pronouns can be **bound** by quantifiers
  Every boy drinks milk with his lunch

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# Types of Referring Expressions

indefinite NPs: used to introduce new entities to discourse
 Waiter, there's a fly in my soup.

- · definite NPs: used to refer to an identifiable entity
- Yes, sir, the fly is doing the backstroke.
- The Trailblazers are in rebuilding mode.
- · Pronouns are a form of definite reference, usually to
- highly salient referents
- · Reflexive pronouns, e.g. himself, herself
- Demonstrative pronouns, e.g. this or that
- One anaphora, has properties of both indefinite and definite reference
  - · Everybody has cell phones these days, but John doesn't want one.

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# Other Kinds of Reference

- Inferable reference: referent not explicitly mentioned, but inferable
  - We climbed Mt. Shasta, but the summit was somewhat disappointing.
  - Part/whole relations, and the results of processes:
- After raking the yard, put *the leaves* in a bag and put it at the curb • Discontinuous sets: *pairwise* reading
- John gets letters from his aunt, and Jimmy gets letters from his cousin. They love getting them.
- Generic reference: general classes of previously mentioned entities
- I had a pickle with lunch. It's my favorite vegetable.
- These make an already difficult problem harder

### **Co-reference Constraints**

- Agreement: Number, Person, Case, Gender. Violations:
   Number: Mary met Mel Gibson. They didn't like him.
- · Person: Mary met Mel Gibson. You didn't like him.
- Case: Mary met Mel Gibson. She didn't like he.
- Gender: Mary met Mel Gibson. She didn't like her.

#### Syntactic constraints

- John likes himself. (himself=John)
- John likes him. (him /= John)
- Bill said that John likes himself. (himself=John)
- Bill said that he likes himself. (himself=he)

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### NP Co-Reference

- Much literature on pronoun co-reference resolution
- Non-pronoun NP co-reference is also a fairly difficult problem
- Content in NPs that can provide clues to co-reference
   Overlap in words between expressions, e.g. "Shaquille O'Neal" and
   "Shaq"
- Inferable features, such as gender and animacy
- Definiteness

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The Role of Co-reference in IE

#### Objects involved in relevant events and relationships are referred to in many different ways and often at widely separate locations in a text

Motor Vehicles International Corp. announced a major management shakeup. MVI said its CEO had resigned. The big automaker is attempting to regain market share. It will announce significant losses for the 3<sup>rd</sup> quarter. A company spokesman said the company will be moving their operations...MVI, the first automaker to announce quarterly results, is the biggest American auto exporter to Latin America.

#### John Simon, Chief Financial Officer of Prime Corp. since 1986, saw his pay jump 20%, to \$1.3 million, as the 37-year-old also became the financial-services company's president. Coreference System [<sub>Js</sub> John Simon], [<sub>Js</sub> Chief Financial Officer], of [<sub>rc</sub> Prime Corp.] since 1986, saw [<sub>Js</sub> his] pay jump 20%; to \$1-3 million, as [<sub>Js</sub> the 37year-old] also became [<sub>rc</sub> the financial services company]'s [<sub>Js</sub> president].

Co-reference System [from Cardie and Wagstaff (1999)]

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# Syntactic Analysis in IE

- Generally directed toward shallow, simple parses of core constituents
- · Semantic analysis involves only ground propositions
- Prepositional attachment only for arguments of domainrelevant verbs
- Locative and temporal adverbials processed, others ignored

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# IE Evaluation Metrics • Precision (P) $Precision = \frac{\# \text{ correct answers}}{\# \text{ answers produced}}$ • Recall (R) $Recall = \frac{\# \text{ correct answers}}{\# \text{ total possible corrects}}$ • F-measure $F = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$

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   Co-reference Resolution