EECS 498-004: Introduction to Natural Language Processing

Instructor: Prof. Lu Wang
Computer Science and Engineering
University of Michigan
https://web.eecs.umich.edu/~wangluxy/

Logistics

• HW4 (last homework) is out! It focuses on NLP applications, and thus only has programming questions (including a bonus question). Due on April 7.
• Will discuss with Dr. Tershia Pinder-Grover on course feedbacks!
• For the rest of this semester:
  • Topics to be covered (in 4 weeks): question answering, dialogue systems (chatbots), discourse (coreference), machine translation
  • Project presentations are scheduled on Apr 19 & 21, team orderings and dates will be randomly decided. Each student will construct short feedbacks (2 points that you like + 1 point for potential improvement) for each team, due on Apr 23.
  • Schedules with future deadlines can be found on course website https://web.eecs.umich.edu/~wangluxy/courses/eecs498_wn2021/eecs498_wn2021.html.

Sample solutions to the bonus question (2.3) in HW 3

• Task: Computing text similarity between two sentences.

Outline

• Text summarization tasks
  • Single vs. multiple documents, query-focused vs. generic, extractive vs. abstractive
  • Summarization pipeline and content selection
  • How to detect salient sentences and salient words
  • Summary evaluation
  • Other aspects of summary quality
  • Information ordering

Text Summarization

• Goal: produce an abridged version of a text that contains information that is important or relevant to a user.

• Summarization Applications
  • outlines or abstracts of any document, article, etc
  • summaries of email threads
  • action items from a meeting
  • simplifying text by compressing sentences

Speech Summarization


Why we need summarization?

• "Summaries as short as 17% of the full text length speed up decision making twice, with no significant degradation in accuracy."
• Does this document contain information that I am interested in?
• Is this document worth reading?
• "Query-focused summaries enable users to find more relevant documents more accurately, with less need to consult the full text of the document." [Mani et al., 2002]

Example: “what is keto diet”

What is the output

• Keywords
• Highlighted information in the input
• Chunks or speech directly from the input or paraphrase and aggregate the input in novel ways
• Modality: text, speech, video, graphics

What to summarize (i.e. input)?

Single vs. multiple documents

• Single-document summarization
  • Given a single document, produce
    • abstract (a paragraph)
    • outline (bullet points)
    • headline (one sentence)

• Multiple-document summarization
  • Given a group of documents (usually relevant and pre-clustered), produce a gist of the content:
    • a series of news stories on the same event (this can be a timeline summarization)
    • a set of web pages about some topic or question (e.g. you want different perspectives on a certain policy or some medical treatment)

Example: Scientific article summarization

• Single-document summarization task:
  • Not only what the article is about, but also how it relates to work it cites → summarize the article with regard to prior work

• Multi-document summarization task:
  • Determine which approaches are criticized and which are supported → summarize articles that cite a given article

  "xx et al. presents an efficient algorithm..." more useful than original paper abstracts
Do we have a focus?
Query-focused Summarization vs. Generic Summarization

- **Generic summarization:**
  - Summarize the content of a document
- **Query-focused summarization:**
  - Summarize a document with respect to an information need expressed in a user query,
  - a kind of complex question answering:
    - Answer a question by summarizing a document that has the information to construct the answer

Summarization for Question Answering or Search Engine: Featured Snippets

- Create snippets summarizing a web page for a query (could be paragraphs)

Looking at the output:
Extractive summarization vs. Abstractive summarization

- **Extractive summarization:**
  - create the summary from phrases or sentences in the source document(s)
  - will not use words that do not appear in the input
- **Abstractive summarization:**
  - express the ideas in the source documents using (at least in part) different words

Extractive summarization

Sample article:
The Trump administration accused Russia on Thursday of engineering a series of cyberattacks that targeted American and European nuclear power plants and water and electric systems, and could have sabotaged or shut power plants off at will.

United States officials and private security firms saw the attacks as a signal by Moscow that it could disrupt the West’s critical facilities in the event of a conflict.

They said the strikes accelerated in late 2015, at the same time the Russian interference in the American election was underway. The attackers had compromised some operators in North America and Europe by spring 2017, after President Trump was inaugurated.

Extractive summarization: sentence-level

Sample article:
The Trump administration accused Russia on Thursday of engineering a series of cyberattacks that targeted American and European nuclear power plants and water and electric systems, and could have sabotaged or shut power plants off at will.

United States officials and private security firms saw the attacks as a signal by Moscow that it could disrupt the West’s critical facilities in the event of a conflict.

They said the strikes accelerated in late 2015, at the same time the Russian interference in the American election was underway. The attackers had compromised some operators in North America and Europe by spring 2017, after President Trump was inaugurated.
Extractive summarization: phrase-level

Sample article:
The Trump administration accused Russia on Thursday of engineering a series of cyberattacks that targeted American and European nuclear power plants and water and electric systems, and could have sabotaged or shut power plants off at will.

United States officials and private security firms saw the attacks as a signal by Moscow that it could disrupt the West's critical facilities in the event of a conflict.

They said the strikes accelerated in late 2015, at the same time the Russian interference in the American election was underway. The attackers had compromised some operators in North America and Europe by spring 2017, after President Trump was inaugurated.

Abstractive Summarization

- Input: Congratulations to Australia for seeing sense and dropping the ridiculous policy of not selecting their best players if they are playing overseas.

- Summary: Australia have seen sense by revamping their overseas selection policy.

- How does a model achieve this?

Most current and “successful” systems

- Use shallow analysis methods (frequent words)
  - Rather than full understanding

- Work by sentence selection
  - Identify important sentences and piece them together to form a summary

Outline

- Text summarization tasks
  - Single vs. multiple documents, query-focused vs. generic, extractive vs. abstractive

- Summarization pipeline and content selection
  - How to detect salient sentences and salient words
  - Summary evaluation
  - Other aspects of summary quality
  - Information ordering
Summarization: Three Stages
1. **content selection**: choose sentences to extract from the document
2. **information ordering**: choose an order to place them in the summary
3. **sentence realization**: clean up the sentences (e.g., removing redundancy)

Basic Summarization Algorithm (extractive)
1. **content selection**: choose sentences to extract from the document
2. **information ordering**: just use document order
3. **sentence realization**: keep original sentences

Unsupervised content selection
- What words or sentences can be considered as important?

Frequency as document topic proxy
- Simple intuition, look only at the document(s)
  - Words that repeatedly appear in the document are likely to be related to the topic of the document (single document)
  - Sentences that repeatedly appear in different input documents represent themes in the input (multiple documents)

Frequency as document topic proxy
- Simple intuition, look only at the document(s)
  - Words that repeatedly appear in the document are likely to be related to the topic of the document (single document)
  - Sentences that repeatedly appear in different input documents represent themes in the input (multiple documents)
  - But what appears in other documents is also helpful in determining the topic
    - Background corpus probabilities/weights for word
What is an article about?

- Word probability/frequency
  - Proposed by Luhn (Luhn 1958)
  - Frequent content words would be indicative of the topic of the article
  - In multi-document summarization, words or facts repeated in the input are more likely to appear in human summaries [Nenkova et al., 2006]

Main steps in sentence selection according to word probabilities

- Step 1: estimate word weights (probabilities)
- Step 2: estimate sentence weights
- Step 3: choose best sentence
- Step 4: update word weights
- Step 5: go to step 2 if length not reached
Obvious shortcomings of the pure frequency approaches

- Does not take account of paraphrases or related words
  - Bombing – explosion
  - Gadhafi – Libya
- Does not take into account evidence from other documents
  - Function words: prepositions, articles, etc.
  - Domain words: “cell” in cell biology articles
- Does not take into account many other aspects (relations, events, etc.)!
  - Semantic in general!

Salient words

- Intuition dating back to Luhn (1958):
  - Choose sentences that have salient or informative words
- Two approaches to defining salient words
  1. tf-idf: weigh each word \( w \) in document \( j \) by \( \text{tf-idf} \)
     \[ \text{weight}(w_j) = \frac{\text{tf}_j \times \text{idf}_i}{\text{tf}_i} \]
  2. topic signature: choose a smaller set of salient words
     - log-likelihood ratio (LLR) test (Luhn 1993), Lin and Hovy (2000)

Example input and associated topic words

- Input for summarization: articles relevant to the following user need

**Title:** Human Toll of Tropical Storms Narrative: What has been the human toll in death or injury of tropical storms in recent years? Where and when have each of the storms caused human casualties? What are the approximate total number of casualties attributed to each of the storms?

**Topic Words**
- Death, suicides, hurricanes, storm, non-violent, insured, financial, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insured, insu...
Formalizing the problem of identifying topic words

- Given
  - t: a word that appears in the input
  - T: cluster of articles on a given topic (input)
  - NT: articles not on topic T (background corpus)

- Decide if t is a topic word or not
- Words that have (almost) the same probability in T and NT are not topic words

\[ H_0: P(T) = P(NT) = p \ (t \text{ is not a descriptive term for the topic}) \]
\[ H_1: P(T) = p_1 \text{ and } P(NT) = p_2 \text{ if } p_1 > p_2 \ (t \text{ is a descriptive term}) \]

Computing probabilities

- View a text (i.e. a sequence of words) as a sequence of Bernoulli trials

- A word is either our term of interest t or not

\[ k(E, N, p) = \binom{k}{N} p^k (1-p)^{N-k} \]

Testing which hypothesis is more likely: log-likelihood ratio test

\[ \lambda = \frac{\text{Likelihood of the data given } H_1}{\text{Likelihood of the data given } H_2} \]

-2 log \( \lambda \) has a known statistical distribution: chi-square

More information can be found: [https://en.wikipedia.org/wiki/Likelihood_ratio_test](https://en.wikipedia.org/wiki/Likelihood_ratio_test) (not required for this course)

Unsupervised content selection

- Topic signatures are assigned with weight of 1

\[ \text{weight}(w) = \begin{cases} 1 & \text{if } -2\log \lambda(w) > 10 \\ 0 & \text{otherwise} \end{cases} \]

\[ \text{Confidence level at 0.001} \]

Topic signature-based content selection with queries

- Choose words that are informative either
  - by log-likelihood ratio (LLR) test
  - or by appearing in the query (if there is a question)

\[ \text{weight}(w) = \begin{cases} 1 & \text{if } -2\log \lambda(w) > 10 \\ 0 & \text{otherwise} \end{cases} \]

\[ \text{(could learn more complex weights)} \]

- Weigh a sentence (or window) by weight of its words:

\[ \text{weight}(s) = \sum_{w \in S} \text{weight}(w) \]
How to do supervised content selection?

• Given:
  - a labeled training set of good summaries for each document
• Align:
  - the sentences in the document with sentences in the summary
  - Or ask human to select sentences
• Extract features
  - position (first K sentence?)
  - length of sentence
  - word informativeness, cue phrases
• Train
  - a binary classifier (put sentence in summary? yes or no)

Problems:

• hard to get labeled training data (sometimes only abstractive summaries are available)
• alignment difficult
• even the same person would select different sentences if she performs the task at different times
• performance not better than unsupervised algorithms

So in practice:

• Unsupervised content selection is more common

Outline

Text summarization tasks
  - Single vs. multiple documents, query-focused vs. generic, extractive vs. abstractive
Summary evaluation
  - Other aspects of summary quality
  - Information ordering

A ROUGE example:

Q: “What is water spinach?”

Human 1: Water spinach is a green leafy vegetable grown in the tropics.
Human 2: Water spinach is a semi-aquatic tropical plant grown as a vegetable.
Human 3: Water spinach is a commonly eaten leaf vegetable of Asia.

• System answer: Water spinach is a leaf vegetable commonly eaten in tropical areas of Asia.

• ROUGE-2 = \( \frac{3 + 3}{10 + 10 + 9} = \frac{12}{29} = .43 \)

Outline

Text summarization tasks
  - Single vs. multiple documents, query-focused vs. generic, extractive vs. abstractive
Summary evaluation
  - Other aspects of summary quality
  - Information ordering

Evaluating Summaries: ROUGE

Human 1: Water spinach is a green leafy vegetable grown in the tropics.
Human 2: Water spinach is a semi-aquatic tropical plant grown as a vegetable.
Human 3: Water spinach is a commonly eaten leaf vegetable of Asia.

• System answer: Water spinach is a leaf vegetable commonly eaten in tropical areas of Asia.

ROUGE (Recall Oriented Understudy for Gisting Evaluation)

\[ \text{ROUGE} = \frac{\sum_{n=1}^{m} \min(\text{count}(n, X), \text{count}(n, S))}{\sum_{n=1}^{m} \text{count}(n, S)} \]

- Intrinsic metric for automatically evaluating summaries
- Not as good as human evaluation (e.g. “Did this answer the user’s question?”)
- But much more convenient, and still used nowadays!
- Given a document D, and an automatic summary X:
  1. Have N humans produce a set of reference summaries of D
  2. Run system, giving automatic summary X
  3. What percentage of the bigrams from the reference summaries appear in X?

- How to detect salient sentences and salient words
  - abstractive
  - focused vs. generic, extractive vs. abstractive
  - Single vs. multiple documents, query

Outline

Text summarization tasks
  - Single vs. multiple documents, query-focused vs. generic, extractive vs. abstractive
Summary evaluation
  - Other aspects of summary quality
  - Information ordering
How to measure redundancy?

Author JK Rowling has won her legal battle in a New York court to get an unofficial Harry Potter encyclopedia banned from publication.

A U.S. federal judge in Manhattan has sided with author J.K. Rowling and ruled against the publication of a Harry Potter encyclopedia created by a fan of the book series.

Sample features:
- Frequency of unigrams or bigrams
- Word overlaps between sentences
- Further consider synonyms (e.g. using WordNet)
- Embedding-based text similarity between sentences

How to measure fluency (or ungrammaticality)?

• A fluent sentence: The new legal classification will entitle the workers to more pay and benefits.

• Less fluent sentences: The the new legal classification will entitle will entitle the workers to more pay and benefits.
  - Sample features: repetition of unigrams and bigrams

How to measure fluency (or ungrammaticality)?

• A fluent sentence: The new legal classification will entitle the workers to more pay and benefits.

• Less fluent sentences: The the new legal classification will entitle will entitle the workers to more pay and benefits.
  - Sample features: repetition of unigrams and bigrams
  - Sample features: missing subject, object, or main verb?
Summarization: Three Stages

1. content selection: choose sentences to extract from the document
2. information ordering: choose an order to place them in the summary
3. sentence realization: clean up the sentences (e.g. removing redundancy)

Information Ordering

• In what order to present the selected sentences?
  • An article with permuted sentences will not be easy to understand
  • Very important for multi-document summarization
  • Sentences coming from different documents

Information Ordering

• Chronological ordering:
  • Order sentences by the date of the document (for summarizing news)
  (Barzilay, Elhadad, and McKeown 2002)
• Coherence:
  • Choose orderings that make neighboring sentences similar (by cosine).
  • Choose orderings in which neighboring sentences discuss the same entity
  (Barzilay and Lapata 2007)
• Topical ordering
  • Learn the ordering of topics in the source documents

Automatic summary edits: advanced topics

• Some expressions might not be appropriate in the new context
• References:
  • Putin
  • Russian Prime Minister Vladimir Putin
• Discourse connectives
  • However, moreover, subsequently
• Requires more sophisticated NLP techniques

Before and After

Pinochet was placed under arrest in London Friday by British police acting on a warrant issued by a Spanish judge. Pinochet has immunity from prosecution in Chile as a senator-for-life under a new constitution that his government crafted. Pinochet was detained in the London clinic while recovering from back surgery.

Gen. Augusto Pinochet, the former Chilean dictator, was placed under arrest in London Friday by British police acting on a warrant issued by a Spanish judge. Pinochet has immunity from prosecution in Chile as a senator-for-life under a new constitution that his government crafted. Pinochet was detained in the London clinic while recovering from back surgery.

Future Directions: Knowledge-based and Advanced Systems

• Discourse information -> coherent summaries
• Use external lexical resources -> redundancy detection
• Wordnet, adjective polarity lists, opinion
• Using machine learning models -> neural network and reinforcement learning
• Towards abstractive summarization
Future Directions: Knowledge-based and Advanced Systems

- Discourse information
  - Coherent summaries
- Use external lexical resources
  - Redundancy detection
  - Wordnet, adjective polarity lists, opinion
- Using machine learning
  - Neural network and reinforcement learning
- Towards abstractive summarization
- Correctness of summaries

Academic paper on women in STEM:

- 19 women
- Role of women in high-level positions and contributions to scientific advancements
- Challenges faced by women in STEM fields
- Strategies for increasing representation and recognizing female contributions
- Importance of diversity and inclusion in education and research