Summarization

• **Summarization**: *n.* the act of producing a shortened version of a text or collection of texts (i.e., a *summary*) that preserves the most important/meaningful/relevant aspects.
Examples of summaries

Russia fights Napoleon and Natalia likes Boris.

Don’t sit on a wall if you’re an egg.

Gregor turns into a bug.

Girl kills a woman, steals her shoes, then kills her sister.
Headline news

• News articles are often shortened to one or two sentences. These summaries:
  • convey the most important aspects of their articles,
  • are often collected together in a group of summaries for easy scanning by the reader.
Abstracts

• Abstracts are often author-generated and time-saving.

An Incremental Interpreter for High-Level Programs with Sensing

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Abstract

Like classical planning, the execution of high-level agent programs requires a reasoner to look all the way to a goal state before even a single action can be taken in the world. This entails a serious problem in practice for large programs. Furthermore, the problem is compounded in the presence of sensing actions which provide necessary information, but only after they are executed in the world. To deal with this, we propose a new method for encoding high-level programs and new high-level language constructs to deal with sensing actions. This method is the only practical way to deal with large agent programs containing both non-determinism and sensing.

Introduction

In [4] it was argued that when it comes to providing high level control to autonomous agents or robots, the notion of high-level program execution offers an alternative to classical planning that may be more practical in many applications. Briefly, instead of looking for a sequence of actions $a$ such that

$$\text{Actions} \vdash \text{Legal}(\langle a, S_a \rangle) \land \phi(\langle a, S_a \rangle)$$

where $\phi$ is the goal being planned for, we look for a sequence $\alpha$ such that

$$\text{Actions} \vdash \text{Do}(\langle \alpha, S_\alpha \rangle, \langle a, S_a \rangle)$$

to find a sequence with the right properties. This can involve considerable search when $\delta$ is very nondeterministic, but much less search when $\delta$ is more deterministic. The feasibility of this approach for AI purposes clearly depends on the expressive power of the programming language in question. In [4], a language called $\text{ConGolog}$ is presented, which in addition to non-determinism, contains capabilities for sequence, iteration, conditions, concurrency, and prioritized interrupts. In this paper, we extend the expressive power of $\text{ConGolog}$ by providing an interpreter that controls the execution of nondeterministic, and by making provision for sensing actions. To do so in a way that will be practical even for very large programs requires introducing a different style of on-line program execution.

In the rest of this section, we discuss on-line and on-line execution informally, and show why sensing actions and non-determinism together can be problematic. In the following section, we formally characterize program execution in the language of the situation calculus. Next, we describe an incremental interpreter for $\text{ConGolog}$ that is correct with respect to this specification. The final section contains discussion and conclusions.

Off-line and On-line execution

To be compatible with planning, the $\text{ConGolog}$ interpreter presented in [4] executes in an on-line manner, in the sense that it must find a sequence of actions constituting an entire legal execution of a program before actually executing any of them in the world. Consider, for example, the following program:
Kinds of summaries

• Summaries can be produced according to several features.
  • **Perspective:** whether the summary is **informative** on its own or if it is merely meant to be **indicative**.
  • **Composition:** whether the summary is **extracted** directly from the source or **synthesized** from scratch.
  • **Orientation:** whether the **author’s view** is preserved or if the summary reflects the **user’s interest**.
  • **Source:** whether we summarize a **single** document or **multiple** documents.
  • **Background:** whether we can assume that the reader has **prior knowledge** or not.
Summarization by extraction

• **Extractive summarization** involves identifying **important sections** in the original text, and **copying** those sections into the summary.

• e.g., The review next week will be *mostly* an extractive summary of the course.
  • i.e., important slides will be extracted from other lectures and agglutinated together.
Summarization by extraction

How do we determine which sentences are relevant?

From Jurafsky & Martin
Determining relevance

• The relevance of sentences and phrases within the text can be approximated by:

1. **Position:** The location of the phrase in the document.
2. **Cues:** The presence of certain words that indicate relevance (e.g., “crucially”, “in conclusion”).
3. **Cohesion:** The distribution of words and their co-occurrences across the document.
4. ...
1. Position-based method

- Important sentences tend to occur in predictable positions within paragraphs and documents.
  - Baxendale (1958) found that in 85% of 200 paragraphs, the most important sentence was also the first.
  - In the news domain, early paragraphs are often very important.
1. Optimum position policy (\(\mathcal{P}\))

- **Claim**: Important sentences are located at positions that are **genre-dependent**; these positions can be determined automatically through training (Lin and Hovy, 1997).

- **Corpora**: 13,000 newspaper articles (ZIFF corpus) and the Wall Street Journal.

- **Step 1**: For each article, determine the overlap between its **index terms** and its sentences.

- **Step 2**: Determine a *partial ordering* over the locations where sentences contain important words.
1. Optimum position policy (OPP)

• The OPP for the ZIFF corpus is:
  \[ T \geq P_2S_1 \geq P_3S_1 \geq P_2S_2 \geq \{P_4S_1, P_5S_1, P_3S_2\} \]
  where \( T = \) title, \( P = \) paragraph, and \( S = \) sentence.

• The OPP for the Wall Street Journal is:
  \[ T \geq P_1S_1 \geq P_1S_2 \geq \cdots \geq P_2S_1 \geq \cdots \]

• By taking the most important 10% of a document according to these orderings, we can cover 91% of the salient words in that document.
2. Cue-phrase method

• Important sentences often contain ‘**bonus phrases**’, e.g., ‘significantly’, ‘in this paper, we show’, and ‘in conclusion’.
  • Unimportant sentences contain ‘**stigma phrases**’ such as ‘hardly’, ‘incidentally’, and ‘ongoing’.

• These cue phrases can be detected automatically (Kupiec et al., 1995; Teufel and Moens, 1997).

• We **increment** a **sentence score** for each **bonus** phrase, and **decrement** its score for each **stigma** phrase.
2. Which words are cues?

• Liu and Hovy (1998) scored words $w$ in ‘high-yield’ sentences from newspaper and scientific publications according to two measures:

  • $S_1(w)$ is the count of $w$ in the summary (e.g., abstract) divided by its total occurrence in a document.

  • $S_2(w) = S_1(w) \cdot \frac{d_f w}{D}$ where $D$ is the total number of training documents, and $d_f w$ is the number of documents in which the word $w$ appears.
2. Cue-phrase method

- Results: the following phrases are good ‘bonus’ cue phrases:

<table>
<thead>
<tr>
<th>Method 1</th>
<th>Method 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$ phrase</td>
<td>$S_2$ phrase</td>
</tr>
<tr>
<td>7.666 $this$ paper presents</td>
<td>3.432 $in$ this paper</td>
</tr>
<tr>
<td>7.666 $machine$ learning algorithm</td>
<td>2.889 $this$ paper we</td>
</tr>
<tr>
<td>6.909 $present$ the result</td>
<td>2.266 section conclusion</td>
</tr>
<tr>
<td>6.888 $paper$ we have</td>
<td>2.279 $a$ set of</td>
</tr>
<tr>
<td>6.340 $this$ paper $we$</td>
<td>2.044 $the$ result of</td>
</tr>
</tbody>
</table>
3. Cohesion-based methods

- Important sentences and paragraphs are highly ‘connected’ entities in larger **semantic structures**.
  - Important concepts occur more frequently in important sentences.

- How to determine cohesion?
  - Word co-occurrence,
  - Local grammatical relations,
  - Co-reference,
  - Lexical similarity.
3. Cohesion: word co-occurrence

- Apply IR methods at the document level.
  - Where IR has **documents within collections**, now we have **paragraphs within documents**.
  - Use traditional IR-based word-similarity measures to determine which paragraph is related to the most other paragraphs – that paragraph is the most salient.
3. Cohesion: lexical chains

• **Lexical chain**: *n.* a sequence of *related* words that can span an entire text. Lexical chains can provide context for the resolution of *ambiguous* terms.
  e.g., *Toronto → capital → city*

• The lexical chains method uses the assumption that important sentences are traversed by *strong* chains, $C$.
  • $\text{Strength}(C) = \text{length}(C) - \text{numDistinctWords}(C)$
    (Barzilay and Elhadad, 97).
  • Take the strongest chains, and copy the first sentences spanned by these chains into the summary.
3. Cohesion: lexical chains example

- Based on Morris and Hirst (1991)

> But Mr. Kenny’s move speeded up work on a **machine** which uses **micro-computers** to control the rate at which an **anaesthetic** is pumped into the blood of **patients** undergoing **surgery**. Such **machines** are nothing new. But Mr. Kenny’s **device** uses two **personal-computers** to achieve much closer monitoring of the **pump** feeding the **anaesthetic** into the **patient**. Extensive testing of the **equipment** has sufficiently impressed the authorities which regulate **medical equipment** in Britain, and, so far, four other countries, to make this the first such **machine** to be licensed for commercial sale to **hospitals**.
3. Cohesion: co-reference

- **Co-reference**: *n.* when multiple expressions refer to the same entity or event.
  
  e.g., *Daniel Turnip* ate a cat that *he* stole from *a small child*. *The temporary President* laughed at *the child*.

- Important sentences are those that are traversed by a large number of **co-reference chains**.
  - A preference is placed on those chains that traverse the title or first paragraph of a document.
Now what?

- So we have three ways to rank sentences as candidates for extraction.

- How do we actually do the extraction?
Naïve Bayes classification

• We can treat summarization as a sequence of binary classification problems:
  • Every sentence is either in or out of the summary.

• Bayes’ decision rule is to select the outcome that is most probable, given contextual features, $f_i$:

\[
\max \left( P(s \in \text{summary} | f_1 \ldots f_k), \right. \\
\left. P(s \notin \text{summary} | f_1 \ldots f_k) \right)
\]

• **Question**: How can we rewrite $P(\sigma | f_1 \ldots f_k)$ to make it easier to measure? **Hint**: consider the title of this slide.
Naïve Bayes classification

• Recall **Bayes’ Theorem** (aka Bayes’ Rule):

$$P(\sigma | f_1 \ldots f_k) = \frac{P(f_1 \ldots f_k | \sigma)P(\sigma)}{P(f_1 \ldots f_k)}$$

• We assume that all features of relevance are conditionally independent,

$$P(f_1 \ldots f_k | \sigma) = \prod_{i \leq j \leq k} P(f_j | \sigma)$$

• And we can use relative frequency in annotated corpora for learning $P(f_j | \sigma)$ using **maximum likelihood estimation**.
Controlling summary length

• Alternatively, we can control the length of our summary by simply computing

\[
\arg\max_{s_i} P(s_i \in \text{summary} | f_1 \ldots f_k)
\]

over all sentences \(s_i\) in the original document and repeating until either

• we’ve extracted a predefined number of sentences, or
• the best probability of a new sentence is below some threshold.
Aspects of extractive summarization

• Summaries produced by extraction can be hard to read, misleading, or incoherent.

• If a pronoun in an extracted sentence (e.g., ‘he’) refers to an entity in a previous sentence that is not extracted, that pronoun may be impossible to resolve by the reader.

• Discourse or argument connectives can become inappropriate in summaries. For example, it would be very odd if the first sentence in a summary began with ‘Finally’.

• Parts of extracted sentences can be unimportant.
Aspects of extractive summarization

• Extractive summarization can be improved.
  • Rhetorical structure can be used to determine relevance.
  • **Cut-and-paste** summarization extracts **phrases** rather than sentences and combines those phrases to **synthesize** new, natural-sounding sentences.
• We can **compare** summaries generated from multiple related texts to see which **terms** seem most important.
• We can tweak the features used in extraction by evaluating our summaries within human-based **tasks**.
Evaluation of summarization

• As in other domains, we can evaluate a summarizer extrinsically (within a task) or intrinsically (independent of task).

  • E.g., we might ask subjects to perform time-constrained fact-gathering tasks given documents and:
    • Human-generated summaries,
    • Automatically-generated summaries,
    • No summaries.
  • The speed and correctness of this task constitutes an extrinsic evaluation.
ROUGE

• A commonly used automatic intrinsic evaluation in summarization is ROUGE (Recall-Oriented Understudy for Gisting Evaluation).

• ROUGE is named after and based upon the BLEU metric we saw in statistical machine translation.

• ROUGE automatically scores a machine-generated candidate summary by measuring the degree of its $n$-gram overlap with human-generated summaries (references).
ROUGE-2

- ROUGE-2 fixes the length of $n$-gram overlap at $n = 2$.
- Given $\text{Count}_{\text{match}}(\text{bigram})$ that counts the number of distinct bigrams that occur in both the candidate summary and a given reference $S$ from among all references, $\text{RefSumm}$,

\[
\text{ROUGE-2} = \frac{\sum_{S \in \{\text{RefSumm}\}} \sum_{\text{bigram} \in S} \text{Count}_{\text{match}}(\text{bigram})}{\sum_{S \in \{\text{RefSumm}\}} \sum_{\text{bigram} \in S} \text{Count}(\text{bigram})}
\]

- ROUGE-1 is identical, except it counts unigrams.
ROUGE-2 example

Don’t sit on a wall if you’re an egg.

Horses fail to perform surgery upon an egg.

Humpty Dumpty had a great fall.

• **Candidate:** *An egg falls off a wall.*

\[
ROUGE_2 = \frac{\sum_{S \in \text{RefSumm}} \sum_{\text{bigram} \in S} \text{Count}_{match} (\text{bigram})}{\sum_{S \in \text{RefSumm}} \sum_{\text{bigram} \in S} \text{Count} (\text{bigram})}
\]

(Over all references)

\[
ROUGE_2 \approx \frac{2 + 1 + 0}{8 + 7 + 5} = \frac{3}{20}
\]
Aspects of ROUGE

• ROUGE is measured relative to the number of \( n \)-grams in all references, whereas BLEU was measured relative to the number of \( n \)-grams in the candidate.
• ROUGE is based on a desire to cover the same content as in human summaries.

• Unfortunately, human summarizers often disagree about what information to include in a summary.
  • Overlap between human summaries can be very low.
  • Although it is a useful baseline, ROUGE is often supplemented with other assessment techniques.
Summarizing summarization

- **Extractive** summarizers produce summaries by selecting important/representative sentences from a text.

- The relevance of sentences can be determined by:
  - **Position:** for instance, news articles tend to begin with their most relevant sentences.
  - **Cue words:** words that indicate relevance such as ‘crucially’ can be determined automatically
  - **Cohesion:** Sentences that contain many strong lexical chains or many co-reference chains ought to be similar to the rest of the document.
Miscellany

• Reading (optional): Jurafsky & Martin, sections 23.3, 23.4, 23.5, 23.7

• Some of these slides are based on those of Eduard Hovy, Daniel Marcu, and Gerald Penn.