UTDHLT: COPACETIC System for Choosing Plausible Alternatives

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Task 7: Choice of Plausible Alternatives (COPA)
Outline

- **PROBLEM**

- Architecture

- Features

- Results
The Problem

“The surfer caught the wave.”

What is a surfer?
What does it mean to “catch a wave”?
How are these concepts related?

Given that the surfer caught the wave, is it more likely that “the wave carried her to the shore” or that “she paddled her board into the ocean”?
The Problem

- Given a **two-choice question**, pick the most plausible **cause** or **effect**:

| Question 15 (Find the EFFECT) |
|-------------------------------|----------------|
| Premise: I poured water on my sleeping friend. | |
| Alternative 1: My friend awoke. | |
| Alternative 2: My friend snored. | |

| Question 379 (Find the CAUSE) |
|-------------------------------|----------------|
| Premise: The man closed the umbrella. | |
| Alternative 1: He got out of the car. | |
| Alternative 2: He approached the building. | |
Outline

- Problem
- ARCHITECTURE
- Features
- Results
System Architecture

Composed of two aspects:

1. **Offline**, question-independent, **pre-processing**
   - Pre-processing resources and data

2. **Online question processing**
   - Answers questions using an SVM linear classifier
System Architecture

Preprocessing:
- POS tagging
- Dependency parsing
- Multi-word expression detection
- TimeML event identification
- Brown clustering

Feature Extraction:
- Bi-gram PMI
- Temporal PMI
- Clausal pattern matches
- Polarity comparison

SVM Classifier

Alternatives:
1. Alternative 1
2. Alternative 2
Offline Processing

**Goal:** extract commonsense facts from the English Gigaword corpus.

We used 24 manually crafted patterns targeting specific **syntactic dependency structures** that embodied **causal relationships**.

...his performance brought on much applause...
Offline Processing

**Motivation:** Causality often manifests as a temporal relation (Bethard, 2008; Bethard and Martin, 2008).

**Goal:** Extract temporal information from Gigaword

We used the **TARSQI** Toolkit to automatically provide **TimeML** temporal link annotations. To combat sparsity issues, we clustered temporal events into **3,200 Brown clusters** publicly provided by Turian, 2010.
Online Processing

• Cast the problem into a classification problem
• Used a linear SVM
• Typical preprocessing:
  – PoS and syntactic dependencies (Stanford CoreNLP)
  – Stopwords
  – Multi-word expressions (noun collocations, phrasal verbs)
  – Events (based on PoS)
Online Processing

Questions are converted into two cause-effect pairs.

**Question 15 (Find the EFFECT)**

Premise: I poured water on my sleeping friend.

Alternative 1: My friend awoke.

Alternative 2: My friend snored.

My friend awoke;
I poured water on my sleeping friend

My friend snored;
I poured water on my sleeping friend

We attempt to form a causal bridge from the cause to the effect using four measures or features.

Each feature assesses the perceived strength of the causal relationship using a different measure of causality.
Outline

- Problem
- Architecture
- FEATURES
- Results
COPACETIC Features:

Bigram Relatedness

Bigram Relatedness: measures relatedness between all pairs of bigrams (token-level) in from the cause-effect pair using PMI:

\[ PMI(x; y) = \log \frac{p(x, y)}{p(x)p(y)} \]

Where:

- \( p(x, y) \) is the probability of observing both bigrams in the English Gigaword corpus within a window of 100 tokens
- \( p(x) \) and \( p(y) \) is the probability of observing bigram \( x \) or \( y \) respectively
- Note: up to two tokens are allowed to occur within a single bigram’s occurrence
**COPACETIC Features:**

**Bigram Relatedness**

<table>
<thead>
<tr>
<th>Question 495 (Find the EFFECT)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Premise: The girl wanted to wear earrings.</td>
</tr>
<tr>
<td>Alternative 1: She got her ears pierced.</td>
</tr>
<tr>
<td>Alternative 2: She got a tattoo.</td>
</tr>
</tbody>
</table>

### Alternative 2 PMI’s

<table>
<thead>
<tr>
<th>Concept</th>
<th>PMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>wear earrings, tattoo</td>
<td>-12.77</td>
</tr>
<tr>
<td>wanted wear, tattoo</td>
<td>-14.284</td>
</tr>
<tr>
<td>girl wanted, tattoo</td>
<td>-14.762</td>
</tr>
<tr>
<td>girl, tattoo</td>
<td>-14.859</td>
</tr>
<tr>
<td><strong>MAXIMUM</strong></td>
<td>-12.77</td>
</tr>
</tbody>
</table>

### Alternative 1 PMI’s

<table>
<thead>
<tr>
<th>Concept</th>
<th>PMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>wear earrings, pierced ears</td>
<td>-10.928</td>
</tr>
<tr>
<td>wanted wear, pierced ears</td>
<td>-13.284</td>
</tr>
<tr>
<td>girl wanted, pierced ears</td>
<td>-13.437</td>
</tr>
<tr>
<td>girl, pierced ears</td>
<td>-15.711</td>
</tr>
<tr>
<td><strong>MAXIMUM</strong></td>
<td>-10.928</td>
</tr>
</tbody>
</table>
Temporal Relatedness: measures strength of temporal links from a given cause and effect using PMI:

\[ PMI(x; y) \equiv \log \frac{p(x, y)}{p(x)p(y)} \]

Where:
- \( x \) is a cause event
- \( y \) is an effect event
- \( p(x, y) \) is the probability that \( x \) is temporally related to \( y \)
- \( p(x) \) is the probability that \( x \) begins any temporal link
- \( p(y) \) is the probability that \( y \) ends any temporal link
COPACETIC Features:
Temporal Relatedness

<table>
<thead>
<tr>
<th>Question 468 (Find the CAUSE)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Premise:</td>
<td>The dog barked.</td>
</tr>
<tr>
<td>Alternative 1:</td>
<td>The cat lounged on the couch.</td>
</tr>
<tr>
<td>Alternative 2:</td>
<td>A knock sounded at the door.</td>
</tr>
</tbody>
</table>

**Alternative 1 PMI’s**

<table>
<thead>
<tr>
<th>lounge, bark</th>
<th>5.60436</th>
</tr>
</thead>
</table>

**TOTAL**

| 5.60436 |

**Alternative 2 PMI’s**

<table>
<thead>
<tr>
<th>knock, bark</th>
<th>5.77867</th>
</tr>
</thead>
</table>

| sound, bark | 5.26971 |

**TOTAL**

| 11.04838 |
COPACETIC Features:
Causal Dependency Structures

We use **casual dependency structures** to attempt to judge the strength of **direct causal relatedness**.

<table>
<thead>
<tr>
<th>Question 490 (Find the EFFECT)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Premise:</td>
</tr>
<tr>
<td>Alternative 1:</td>
</tr>
<tr>
<td>Alternative 2:</td>
</tr>
</tbody>
</table>

Predicts **Alternative 1** because **won** has **15** occurrences in which patterns detected it directly causing **rich**, and only **5** in which it caused **owed**.
COPACETIC Features:

Polarity Comparison

Is a **positive** premise more related to a **positive** or **negative** effect?

The **Harvard General Inquirer** (Stone et al., 1966) which assigns a “prior” **polarity** to words regardless of the context.

- “Positive” (+) words assigned a value of **1.0**
- “Negative” (−) words assigned a value of **-1.0**
- “Neutral” or unseen words assigned a value of **0.0**

Select the **least different** alternative to the premise
COPACETIC Features:
Polarity Comparison

<table>
<thead>
<tr>
<th>Question 494 (Find the CAUSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Premise:</strong> The woman became famous.</td>
</tr>
<tr>
<td><strong>Alternative 1:</strong> Photographers followed her.</td>
</tr>
<tr>
<td><strong>Alternative 2:</strong> Her family avoided her.</td>
</tr>
</tbody>
</table>

- Neutral
- Positive
- Negative
Outline

- Problem
- Architecture
- Features

**RESULTS**
Results

Two systems submitted:

– bigram_pmi scored 0.618
– svm_combined scored 0.634

Not statistically significant.

Need to better determine when to apply each measure/feature, as the nature of each question varies significantly.

There is plenty of room for future improvement!
Thank you!
Any questions?

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