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Inferring Narrative Causality between Event Pairs in Films

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Motivation & Background

- To understand narrative, humans draw inferences about the underlying relations between events
- Previous work either focused on "strict" physical causality [2][6], or event co-occurrence [1][3][4], and applied largely to newswire [1][3]
- We focus on Narrative Causality [7][8][9] - 4 types:
  - Physical Causality: Event A physically causes event B to happen
  - Motivational Causality: Event A happens with B as a motivation
  - Psychological Causality: Event A brings about emotions (expressed in event B)
  - Enabling Causality: Event A creates a state or condition for B to happen, A enables B

Frodo leaps to his feet and pushes his way towards the bar. Frodo **grabs** Pippin's sleeve, **spilling** his beer. Pippin **pushes** Frodo away...he **stumbles** backwards, and **falls** to the floor.

Bilbo leads Gandalf into Bag End... Cozy and cluttered with souvenirs of Bilbo's travels. Gandalf has to **stoop** to **avoid** hitting his head on the low ceiling. Bilbo hangs up Gandalf's hat on a peg and trots off down the hall. Bilbo disappears into the kitchen as Gandalf **looks** around.. **enjoying** the familiarity of Bag End... He **turns**, **knocking** his head on the light and then walking into the wooden beam.

Figure 1: Lord of the Rings, Fantasy Genre

Event Pair	Causality Type
grab - spill	Physical
push - stumble	Physical
push - fall	Physical
stoop - avoid	Motivational
look - enjoy	Psychological
turn - knock	Enabling

Table 1: Event pairs from Lord of the Rings scene with their causality types

Data & Method

- **Event**: non-stative verb with its arguments (generalized to person/something)
- **Event Pair:** two ordered events within a same document
- **955 film scene descriptions:**
  - 11 genres (# of films > 100 each genre)
  - 1.2 ~ 6.7 million words each genre
- Causal Potential [2]:

$$CP(e_1, e_2) = PMI(e_1, e_2) + \log \frac{P(e_1 \to e_2)}{P(e_2 \to e_1)}$$

$$\text{where } PMI(e_1, e_2) = \log \frac{P(e_1, e_2)}{P(e_1)P(e_2)}$$

  - Consists of two terms: pair-wise mutual information (PMI) and relative ordering of bigrams
  - Use a CPC (CP-Combined) measure
    - accounts for different window sizes
    - punishes event pairs from larger window sizes
    - w_{max}: max window size (3 in this paper); CP (e_1, e_2) using window size i

$$CPC(e_1, e_2) = \sum_{i=1}^{w_{max}} \frac{CP_i(e_1, e_2)}{i}$$

Experiments & Results

Download narrative causality event pairs!
https://nlds.soe.ucsc.edu/narrativecausality

High CPC Pairs	Low CPC Pairs
[person] clink [smth] - [person] drink [smth]	[person] strike - [person] give [person] [smth]
[person] beckon - [person] come	*[smth] become - [person] hide*
[person] bend - [person] pick up [smth]	*[person] lift [smth] - [person] cross*
[person] cough - [person] splutter	*[person] force - [smth] show [smth]*
High CPC Pairs	**Rel-gram Pairs**
[person] clear [smth] - [person] reveal [smth]	*[person] clear [smth] - [person] hit [smth]*
[person] embrace - [person] kiss	*[person] embrace [person] - [person] meet [person]*
[person] empty [something] -[person] reload	*[person] empty [smth] - [person] shoot [person]*
[person] stumble - [smth] fall	*[person] stumble upon [person] - [person] take [person]*

Table 2: High vs low CPC pairs from Exp 1, and high CPC vs top Rel-gram pairs from Exp 2, where high CPC pairs gained all Turkers' majority vote on a stronger causality relation

Experiment 1: High vs. Low CPC Event Pairs

- Top 3000 high CPC pairs from all genres - deduplicate to 960 pairs
- Bottom 6000 low CPC pairs from all genres
- Mechanical Turk: which is more likely to have a causal relation?
- Compare high-CPC pair to random low-CPC pair
- 5 Turkers, take majority vote
- Percentage of high-CP pairs labeled as causal: overall - 82.8%; Drama - 82.6%; Fantasy - **90.7%**; Mystery - **87.7%**; ......
- Smaller genres achieve higher causality rate

Experiment 2: CPC vs. Rel-gram [1] Event Pairs

- Rel-gram: *[police] arrest [person] - [person] be charge with [activity]*, with arguments generalized
- Mechanical Turk: which is more likely to have a causal relation?
- 100 random high pairs w. different first events
- Top Rel-gram pairs w. same first event as CPC pairs
- **81%** vote CPC pairs from film, 19% vote Rel-gram

Experiment 3: Narrative Causality Types

- Strong to weak: Physical, Motivational, Psychological, Enabling causality
- 100 random high-CPC pairs with all 5 Turkers' votes in Experiment 1
- Mechanical Turk: choose the strongest narrative causality
- 79% has majority vote: Motivational - 29%; Enabling - 28%; Physical - 13%; Psychological - 9%

Experiment 4: Genre Specific Causality

- 960 top pairs induced using separate genres vs. 960 top pairs induced using all films:
  - More than 70% overlap (with smaller genre sets most causal pairs were learned)
  - Mechanical Turk evaluation of non-overlap pairs shows quality of pairs from all vs. separate genres is similar
- 960 top pairs induced using separate ganres vs. 200 top pairs from camping & storm blogs [5]:
  - Only 2 overlap: *sit - eat*, *play - sing*
  - Causal relations learned from such small sets have topical and event-based coherence

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