Weakly Supervised Induction of Affective Events by Optimizing Semantic Consistency (AAAI 2018)

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Affective Events

Affective Events

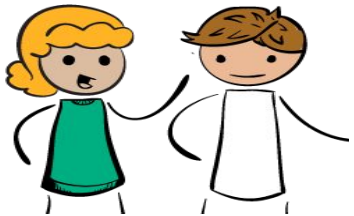
Affective events usually are events that are **stereotypically desirable** (positive) or **undesirable** (negative) for experiencers based on world knowledge.

I went diving last weekend.

That's cool!

*I **broke** my leg this morning.*

Oh, sorry to hear that



More difficult to recognize since polarity is implicit and depend on both predicate and its arguments

Polarity of Affective Events

POSITIVE: events that are desirable, pleasant, enjoyable, and beneficial.

e.g. I went to block party;   I attended the show

NEGATIVE: events that are undesirable, unpleasant,   unenjoyable, and detrimental.

e.g. I got into an argument;   my dog passed away

NEUTRAL: events that are not positive or negative.

e.g.   I open door;   I go;   I see

Problem statement

- Design a weakly supervised method to learn a large set of affective events
- Analyze affective events from the perspective of the experiencer
    - Only first person mentions or his/her family members
    - Does not mention other people

Prior Works

- Connotation of words and word senses (Kang et al. 2014) and connotation frames (Singh and Choi 2016)
  - Infer from writer's and entity's perspective
- Studied +/- effect on events, but not affective in nature (Choi and Wiebe 2014)
  - Baking a cake is positive because cake is being created

Prior Works

- Related to “emotion-provoking events” (Vu et al. 2014) and “major life events extraction” (Li et al. 2014)
  - Do not identify polarity
- Graph-based learning methods for sentiment lexicon induction
  - Most of them aims to learn the prior polarity for individual words (Rao and Ravichandran 2009; Velikovich et al. 2010)

Previous paper - AAAI 2016

Acquiring Knowledge of Affective Events from Blogs Using Label Propagation

- Semantic graph constructed based on discourse relations and event co-occurrence
- Developed an “Event Context Graph” model to induce affective events
  - Uses traditional label propagation algorithm
  - Agent and Theme representation differs since they extract only single words

Contribution of the paper

- Present a manual annotation study of randomly sampled event (40% of cases)
    - 1500 events annotated over - positive, negative, neutral and mixed
- Propose a rich event structure representation
- Present a novel, weakly supervised method for inducing more than 100K affective events from an unannotated story corpus
    - Construct a semantic event graph
    - Iterative learning framework

Event Representation and Extraction

- Events are extracted using dependency relation rules

<I, dropped, my phone, into toilet>

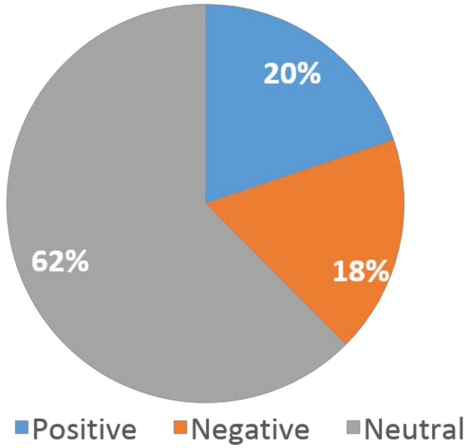
Agent *Predicate* *Theme* *PrepPhrase*

Predicate : each finite verb and may include a particle, a negator
<eat> and <not want to take off>
Theme : <go to beach> vs <go to prison>
Prepositional phrase - closest to Verb phrase

Stanford CoreNLP was used for POS and NER tagging, Active and Passive voice is normalized

Dataset

- Personal Story Corpus: ICWSM 2009 and 2011 Spinn3r data
  - 1,383,425 personal stories using classifier (Gordon and Swanson 2008), resulted in 571,124 events
- Affective event dataset - 571, 424 unique events
  - Events with only first person mention, family members and no other person mentions
  - Frequency > 5



Manual analysis of Affective events

How prevalent are affective events?

- Labeled a randomly selected set of 1500 events
- 3 annotators with Cohen’s kappa (~0.7) and majority labelling
- Observed 38% of them have a +/- polarity

Gold standard data of 1490 events, labelled as POS(20%), NEU(62%), NEG(18%)

Weakly Supervised Induction

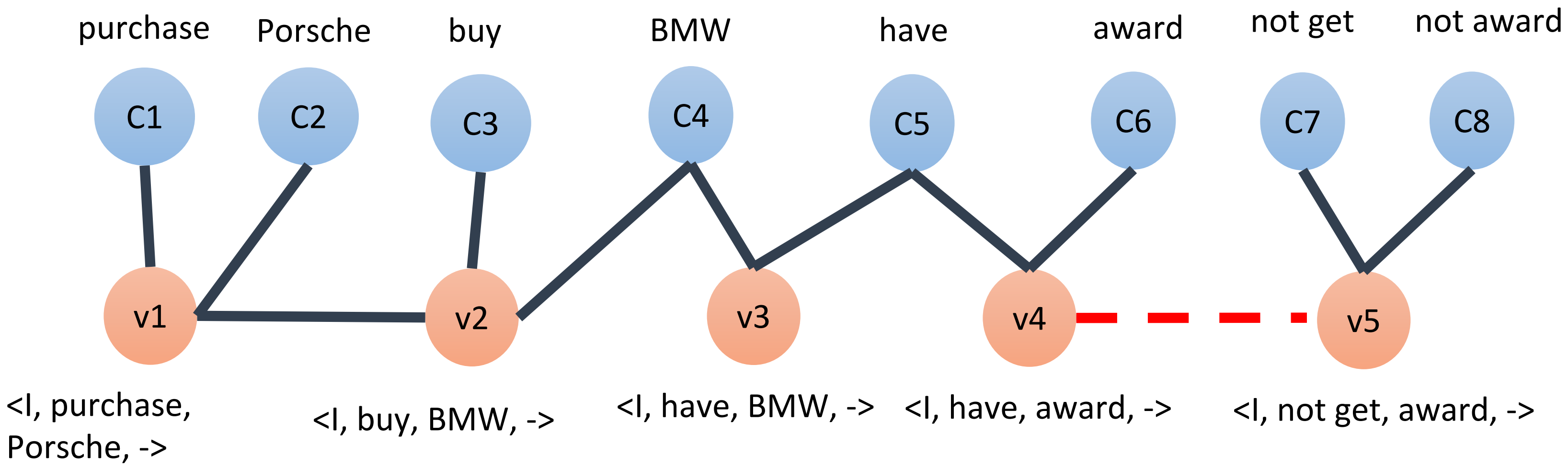
Weakly supervised induction

- Define a graph (V, E) where each node is an event or a component of an event
    - 571,624 event nodes + each event argument <predicate + 3>
    - If predicate is negated, negation attached to each component

- Initialize the polarity of each node using sentiment lexicons as noisy supervision
    - Perform well at detecting affective events with explicit emotions or strong positive/negative terms
    - <I had fun>, <The experience was a disaster>

Semantic Relations Graph - Vertices

- Polarity vector for each node : distribution over 3 polarity values
  - <POS, NEU, NEG>



Semantic Similarity Edges (W_{ij}^{sim})

- Semantically similar events have similar Affective Polarity

"I lost my job" 😥 → *"I got fired"* 😥

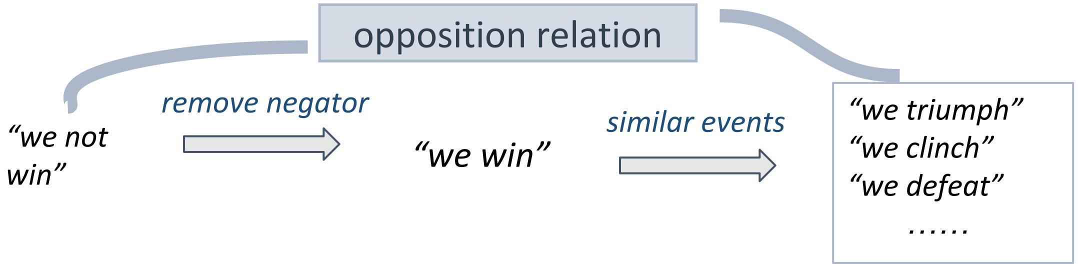
- Compute semantic similarity using event embeddings
  - Average of the Glove embeddings of words in the event expression
- Edge construction : For each node i, the 5 most similar nodes
  - Cosine similarity between two event vectors

Semantic Opposition Edges (W_{ij}^{opp})

- Semantically opposite events have opposite Affective Polarity

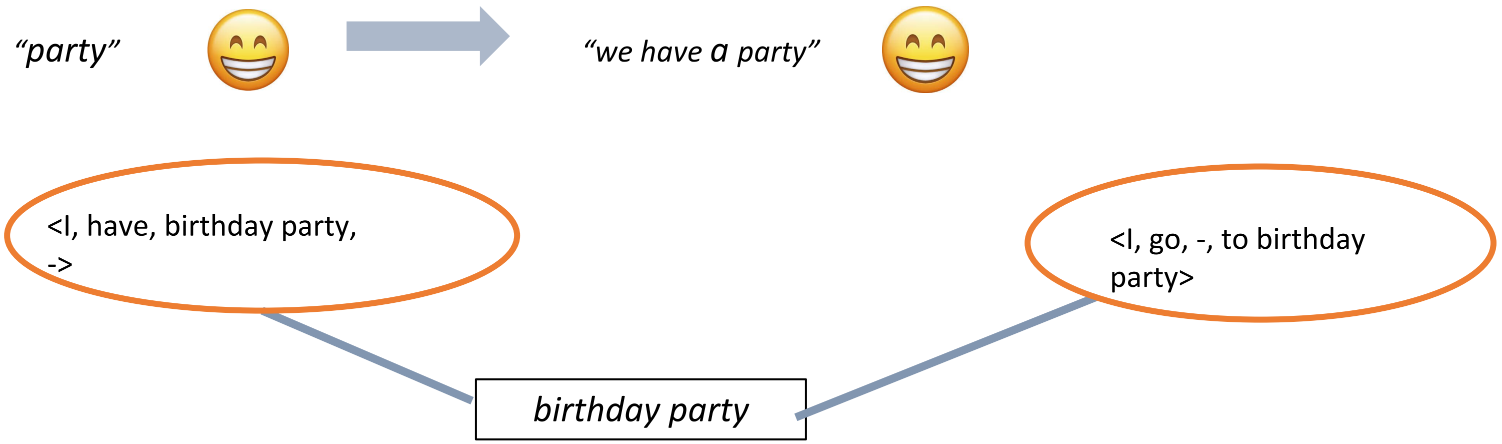
"we win"  → "we didn't win" 

- Identify events with negated predicate. Remove negator and compute embedding
- Edge construction : 10 most similar nodes, in terms of cosine similarity



Event-Component Edges (W_{ik}^{cmp})

- Events and their generalized concepts have similar polarity
- Edge construction: For each node i, create edges with each component (k)
  - Edge weight: 1



Optimizing semantic consistency

Initialization and Semantic consistency metrics

- Empirically observed MPQA lexicon (Wilson, Wiebe and Hoffman 2005) plus an aggregated contextual classifier <POS, NEU, NEG>
  - These initial polarity vector act as anchor for the estimated polarity vector
- Learns to minimize inconsistency in graph
  - Uses KL-divergence to measure inconsistency between 2 polarity vectors
  - Semantic similarity: $D(v_i \,||\, v_j)$
  - Semantic opposition: $D(v_i \,||\, v_j H)$, where H= exchanges the polarity vector's + and - values
- Weight normalization: Row normalization of W(s)

Optimizing Semantic Consistency

$$J_{sc} = \beta \sum_{i=1}^{n} D(v_i || v_i^0) + \sum_{(i,j)} \tilde{W}_{ij}^{sim} D(v_i || v_j) + \sum_{(i,j)} \tilde{W}_{ij}^{opp} D(v_i || v_j H) +$$

Event Initialization

Similarity Edges

Opposition Edges

Final polarity = argmax (<polarity vector>)

Optimizing Semantic Consistency

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Event Initialization

Similarity Edges

Opposition Edges

$$\gamma \sum_{(i,k)} \tilde{W}_{ik}^{cmp} D(v_i || c_k) + \gamma \sum_{(k,i)} \tilde{W}_{ki}^{cmp'} D(c_k || v_i) + \eta \sum_{k=1}^{m} D(c_k || c_k^0)$$

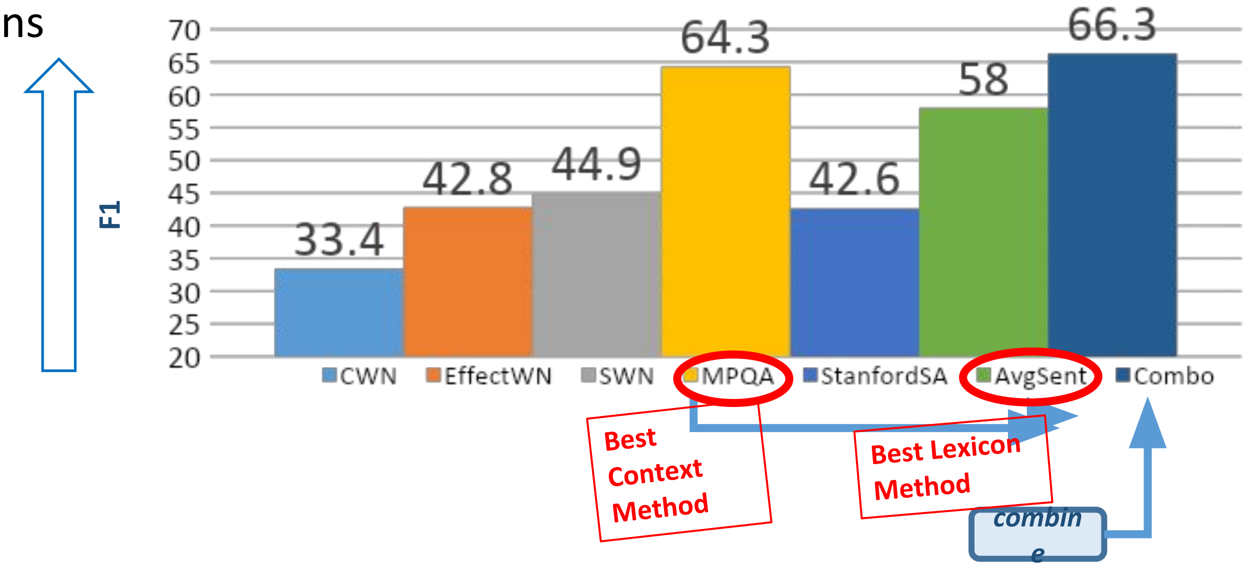
Event-Component Edges

Component Initialization

- Alternatively updates v(event nodes) and c (component nodes)
- Final polarity = argmax (<polarity vector>)

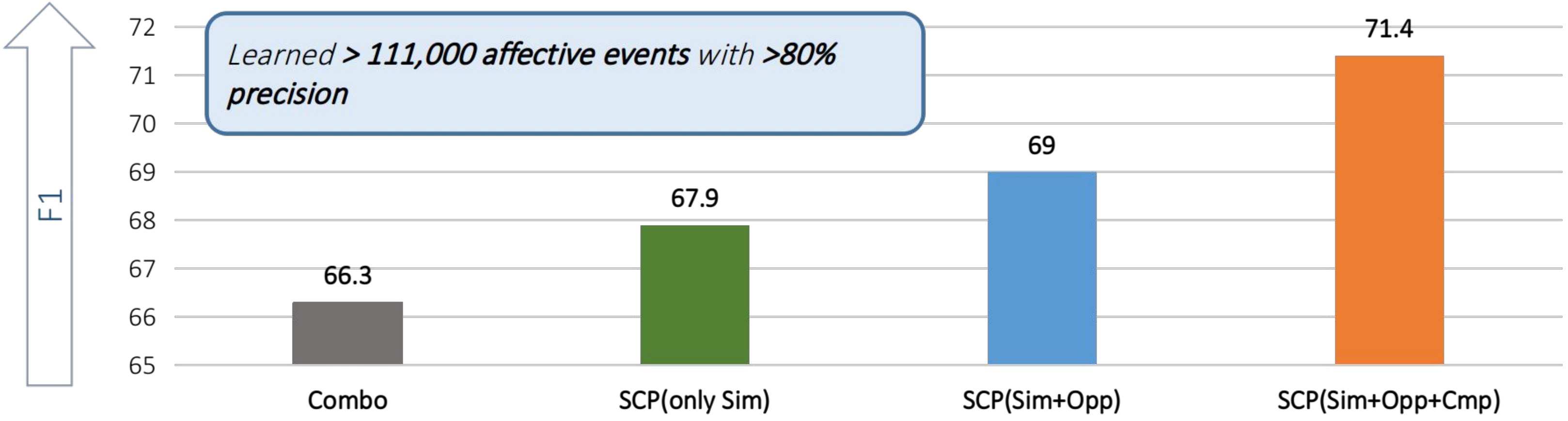
Experiments and results

- Existing Sentiment resources and classifiers
  - Affective Lexicons
  - Event Structure Classifiers Contextual models



Experiments and results

- Semantic Consistency Models



Analysis Results

- Most frequent changes occur. Polarity changed between Combo model to SC model
  - positive or negative polarity to neutral
  - Neutral to negative
- Large shifts from positive/negative to neutral corresponds to precision gains
- Shifts from neutral to negative leads to increased recall for negative polarity

Creation of affective event lexicon

- Assigned polarity value > T (0.5 to 0.7)
  - For T=0.7, Pr = 100, Rec = 18.7, Total events = 37978
  - For T = max, Pr = 75.7, Rec = 55.1, Total events = 175,141
- Both labeled data and affective event data available at http://www.cs.utah.edu/~hbding/affectEventResource.html

Conclusion & Future Work

- Design a novel, weakly supervised semantic consistency model for automatically inducing a high-quality event lexicon
- Proposed model outperforms existing sentiment lexicons and learning methods
- Learns over 100,000 affective events with high precision
  - Recall can be improved (55.1 for positive and 63.3 for negative)

Future Work :

- Increasing Affective event subset: Instead of removing blogs with third person mentions, use discourse structure
- Negation handling in SC graph: determining best scope of negation handling is difficult

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Thank you for your attention