

# Extracting contingent event pairs in blog corpus

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## Abstract

One of the most important tasks in NLP is extraction of the relation CONTINGENT between event pairs i.e deciding whether an event caused another event. We experiment with different measures of establishing this relation as used in previous works (Chao et al., 2013) using a variety of representations (Manshadi et al., 2008). These experiments are conducted on blog stories taken from the domain of travel and sports. Two tasks are used for evaluations: Discriminate and Narrative Cloze.

## 1 Introduction

Any narrative story can be seen as a chain of ordered events. In this project, we would like to focus on extracting the event pairs which are contingent on each other, in an unsupervised data driven fashion. It would be nice to try to understand more about the internal structure of the different types of stories, basically to find out what kinds of action sequences characterize them. Extracting contingent events is a prerequisite in many NLP tasks like text coherence, entailment, question answering and information retrieval (Girju and Brandon, 2009). Previous work shows good results in finding the contingent event pairs from film scenes by modeling the likelihood between events (Chao et al., 2013).

We feel trying to extract such causal chains from personal stories may provide for better common sense reasoning and help in script learning in common scenarios about which

people often blog. Also trying out different event representations could help yield better understanding of which components contribute to the discovery of the CONTINGENT relation between events.

## 2 Related Works

Girju et al. focused on giving a statistical measure to the events that are in causal relationship by defining causal potential (Girju and Brandon, 2009). Chambers et al. defined such events with causal relationships as narrative event chains and came out with different ways of learning (Chambers and Jurafsky, 2008). They also build a new method of identifying event semantics that jointly learns event relations and their participants from unlabeled corpora (Chambers and Jurafsky, 2009). Chiacros solved the same problem by providing a method for identifying a discourse connective between different utterances in text (Chiacros, 2012). Manshadi et al. tried to solve a similar problem by learning a probabilistic model of event sequences using statistical language modeling techniques (Manshadi et al., 2008). Quang Xuan Do et al. followed Chiacros methodology of solving similar problem by feeding discourse connectives and the particular discourse relation in addition to the distributional similarity to identify causal relations between events (Do et al., 2011)

Our hypothesis and methodology is mostly a hybrid of Chao et al. and Manshadi et al. with certain differences. We create a variety of

different event representations and evaluate some of the contingency measures used by others mentioned above and see how they perform for sports and travel stories. We believe that the underlying assumption of temporal coherence and contingency do exist in the sports and travel stories.

### 3 Data

A sample story from our corpus:

This morning my dad, uncle and I went for a short hike around the Short Hill. I had long known that part of the mountain was part of Harpers Ferry National Park, but only last week discovered access to the site . I told my dad about it and he was interested to check it out. Despite the cold drizzley weather we set out, being careful to not injure our selfs stepping into deep piles of leaves as I had the last time I visited the site. Almost immediately we encountered the ruins of an old lime kiln, which sadly I neglected to take a picture. A little further up the trail we came to the ruins of the old River Mill. We then made our way around the Short Hill on an old road bed, catching good views across and up river. That last pic was taken from a 60ft bluff above the river, and though you can't make it out in the picture, good views of Harpers Ferry 5 miles distant were had. Though the hike was short and we only stuck to the shore and did not attempt the mountain it was enjoyable and left me impatient for the spring when i can mount a full expedition of the area. Definitely going to need a machete because the undergrowth is going to be bad, good shoes and a hiking stick will also be necessary on the steep ungraded slopes. Check out my facebook for a few pics from the hike.

The data we are using consists of a number of blog stories divided into two major domains: travel and sports. These stories were taken from The Internet Personal Story Archive(Reid., 2007) which is a collection of blog posts taken from the internet. Stories within each domain are also sub categorized into a number of fine grained topics like hiking, skiing, scuba diving etc. for travel and cricket, soccer, swimming for sports. These two domains were chosen because we think these two are characterized by a set of events that occur similarly in the experiences of different people. The corpus used consists of 353

stories for sports and 444 for travel.

### 4 Event Representations

There are different ways in which an event can be represented. At the core it is an action- a verb. But for the purpose of our task, considering the subject or the object may provide extra information. Thus we experiment with four different event representations: *a) Just the verb b) Verb + Subject+Object c) Verb + Subject d) Verb + Object.*

As an example the following sentence can be seen in any of the 4 forms:

*Ronaldo kicked the ball.*

- a) **Verb + Subj + Obj** : *kick, Ronaldo, ball.*
- b) **Verb + Subj** : *kick, Ronaldo*
- c) **Verb + Obj** : *kick, ball.*
- d) **Verb** : *kick*

Different representations might be helpful in different domains and this why we test them out for both the domains and see which representation is more informative in that context.

### 5 Contingency Measures

For the different representations we calculate three measures of contingency as used in previous works :

**Probabilistic Language Models.** We build statistical language models using the events where we represent each document as a sequence of events(Manshadi et al., 2008). We compute the bigram probabilities of verbs that occur in the document and it is defined as :

$$P(w_1, w_2) = \frac{\text{count}(w_1, w_2)}{\text{count}(w_1)} \quad (1)$$

These probabilities were calculated using the SRILM toolkit with an ngram order of 2 and using *kndiscounts*.

So the corpus is converted to a form where each document is represented as a space delimited sequence of event representation. And

different documents are delimited by a line break.

So for an example document:

*John Doe opened the box. He ate the chocolates.*

The above document would be represented in the following way in the different representations:

- a) **Verb + Subj + Obj**: open|PERSON|box  
eat|PERSON|chocolates.
- b) **Verb + Subj** : open|PERSON  
eat|PERSON.
- c) **Verb + Obj** : open|box eat|chocolates.
- d) **Verb** : open eat.

Thus in this fashion we get the language models which are used to calculate the next two measures.

In addition to this, we also create one skip languages models. This is basically done to capture the CONTINGENT event pairs that span over more than one events. For eg, if a document is represented as a series of events  $e_1, e_2, e_3, e_4$  and  $e_5$  then we create a model considering  $e_1, e_3, e_5$  as a sequence of events and  $e_2, e_4$  as a sequence of another set of events. A language model following the this structure of event representation is created. We interpolate this model with the language model that was defined above for normal bi-gram probabilities.

Given a pair of events  $e_1$  and  $e_2$  present in both original language model and skipped model. The interpolated model is represented as :

$$\lambda P_{normal}(e_1, e_2) + (1 - \lambda) P_{skipped}(e_1, e_2) \quad (2)$$

We tune the value for  $\lambda$  for each of the different types of event representation over a development set.

**Point wise Mutual Information(PMI)** . It is a symmetric measure of two events occurring adjacent to each other in a document.

So this finds the probabilities of two events appearing close to one another but not actually imply causality(Chambers and Jurafsky, 2008; Chambers and Jurafsky, 2009).

The PMI between two events is defined as:

$$pmi(e_1, e_2) = \log \frac{P(e_1, e_2)}{P(e_1)P(e_2)} \quad (3)$$

in which  $e_1, e_2$  are two events.  $P(e_1)$  is the probability that event  $e_1$  occur in corpus :

$$P(e_1) = \frac{count(e_1)}{\sum_x count(e_x)} \quad (4)$$

The joint probability of both events occurring together( $P(e_1, e_2)$ ) is given by :

$$P(e_1, e_2) = \frac{count(e_1, e_2)}{\sum_x \sum_y count(e_x, e_y)} \quad (5)$$

The probabilities required to calculate PMI were obtained from the language models created by SRILM toolkit.

All words in the test data that were not present in the vocabulary of the language models were mapped to the symbol *unk* which is already present in the language model. If a certain bi-gram probability  $P(e_1, e_2)$  to be used in the test data is not present in the language model, then we use the back off weights which is given by :

$$P(e_1, e_2) = P(e_2) * bow(e_1) \quad (6)$$

**Causal Potential.** A more refined measure for causality was proposed by (Girju and Brandon, 2009). They define a manipulation test for annotators trying to judge if event A caused event B.

- (i) Does event A occur before (or simultaneously) with event B?
- (ii) Keeping constant as many other states of affairs of the world in the given text context as possible, does modifying event A entail predictably modifying event B?

Answering yes to both these questions would imply causality.

**CP** is thus defined as :

$$\phi(e_1, e_2) = pmi(e_1, e_2) + \log \frac{P(e_1 \rightarrow e_2)}{P(e_2 \rightarrow e_1)} \quad (7)$$

where  $pmi(e_1, e_2)$  is given by (3).

## 6 Experiment set up and Evaluation

### 6.1 Evaluation

Two major tasks used for evaluation are Discriminate and Narrative Cloze. We used perplexity as an initial measure to find an estimate of how good the language models were.

#### 6.1.1 Discriminate

In this task we generate random permutations of the events of a document and see if the different models assign a higher rating to the random permutations or the original ordering of events.

These ratings are calculated for each different contingency measure:

- $\sum_{i=1}^{n-1} \text{Org\_Order } \phi(e_i, e_{i+1}) > \sum_{i=1}^{n-1} \text{Permuted\_Order } \phi(e_i, e_{i+1})$
- $\sum_{i=1}^{n-1} \text{Org\_Order } \log P(e_i, e_{i+1}) > \sum_{i=1}^{n-1} \text{Permuted\_Order } \log P(e_i, e_{i+1})$

We hope to compare the different contingency measure as well and see whether CP is actually a better measure that both or not.

#### 6.1.2 Narrative Cloze

The cloze task (Taylor, 1953) is used to evaluate a system (or human) for language proficiency by removing a random word from a sentence and having the system attempt to fill in the blank. Depending on the type of word removed, the test can evaluate syntactic knowledge as well as semantic (Chambers and Jurafsky, 2008). Instead of words we are taking out events. Then the plucked out event is placed at each position in the document and the document is rated by each of the contingency measure. The position rated best is

taken to be the predicted position and we calculate the value delta (for each measure) as,

$$\delta = |\text{actual\_position} - \text{predicted\_position}| \quad (8)$$

This delta value is averaged over the number of events in the corpus to get the Mean positional value per event and Mean positional value per document is calculate as :

$$\text{mean\_pos\_score} = \frac{\sum_{i \in \text{docs}} \text{avg}_i}{n} \quad (9)$$

where  $n$  is the number of documents and  $\text{avg}_i$  is defined as :

$$\text{avg}_i = \frac{\sum_{j \in \text{events}(i)} \delta_j}{\text{length}(i)} \quad (10)$$

#### 6.1.3 Perplexity

Perplexity is a way to evaluate language models over test data. It shows how surprised is the model in seeing a new event. Perplexity of a sentence is denoted by :

$$PP_p(S) = 2^{H_p(S)} \quad (11)$$

where  $H_p(S)$  is the cross entropy and its defined as :

$$H_p(S) = \frac{-1}{W_s} * \log_2 p(S) \quad (12)$$

where  $W_s$  is the number of words in the sentence in other words number of bits required to encode the sentence.

Representation	Perplexity
V + S + O	56.0863
V+ S	132.118
V+ O	72.486
V	87.374

Table 1: Initial perplexity results for Travel(67 stories)

Representation	Perplexity
V + S + O	54.9574
V+ S	141.279
V+ O	96.4696
V	95.1299

Table 2: Initial perplexity results for Sports(53 stories)

## 6.2 Experiment set up

We use Stanford CoreNLP(Manning et al., 2014) toolkit to get the annotations. We feed into the parser the entire corpus of stories and yield corresponding XML files which contain necessary annotations. We parse the XML output to get the verbs in their lemmatized form, which are actions and also extract the subject and object of the verb from the dependency parse. We are trying to use the SRILM toolkit for getting the necessary counts and probabilities for each of these measures(Stolcke, ).

The data in both the domains was divided in three parts: train (85%), development (5%) and test (10%). So for travel we have 378 stories for train, 44 for testing and 22 for development. And sports is split into 300 train, 35 test and 17 for development.

## 7 Results and Discussion

We tuned the mixture model which is a linear combination of skip and the original model with the help of  $\lambda$ . We ran them with  $\lambda$  values ranging from 0 to 1 with a *step size* of 0.01 to figure the best possible value for  $\lambda$ . The  $\lambda$  values change for each representation and domain. For travel, the best possible  $\lambda$  value was in the range of 0.77 – 0.82 and for sports it was in the range of 0.75 – 0.85. After tuning the mixture mode with the development set, we run the discriminate task on the original model as well as the mixture model for all the event representations on the with held test test. The tables below show the discriminate and cloze results of all the experiments.

### 7.1 Discriminate Results

Model	Representation	CP				logp			
		Wins	Losses	Ties	Win %	Wins	Losses	Ties	Win %
Original	V+S+O	164	56	5	75.11	178	42	5	<b>81.3</b>
	V+S	184	41	0	81.7	199	26	0	<b>88.4</b>
	V+O	194	24	6	88.8	202	17	6	<b>92.4</b>
	V	186	39	0	<b>82.7</b>	176	49	0	78.2
Combined	V+S+O	164	56	5	76	171	49	5	<b>78.2</b>
	V+S	183	49	0	<b>81.3</b>	176	42	0	78.2
	V+O	184	36	5	84.9	192	28	5	<b>87.6</b>
	V	169	56	0	<b>75.1</b>	155	70	0	68.9

Table 3: Discriminate results for travel stories(225 samples)

Model	Representation	CP				logp			
		Wins	Losses	Ties	Win %	Wins	Losses	Ties	Win %
Original	V+S+O	140	40	0	77.8	161	19	0	<b>89.4</b>
	V+S	158	22	0	87.8	168	12	0	<b>93.3</b>
	V+O	158	22	0	87.8	164	16	0	<b>91.1</b>
	V	153	27	0	85	165	15	0	<b>91.7</b>
Combined	V+S+O	134	46	0	74.4	157	23	0	<b>87.2</b>
	V+S	143	37	0	79.4	156	24	0	<b>86.7</b>
	V+O	151	29	0	83.9	157	23	0	<b>87.2</b>
	V	152	28	0	84.4	157	23	0	<b>87.2</b>

Table 4: Discriminate results for sports stories(180 samples)

It is very evident from the table that the discriminate results of  $\log p$  does better than CP. For travel, its interesting to see that CP for verbs does better than  $\log p$  where as it relatively does bad when compared to  $\log p$  for other representations. This could be because since there are a lot of *unks*'s mapped in the representation which shows how sparse the representations are and that impacts the difference in performance of discriminate. For sports, the  $\log p$  simply outperforms CP in every representation which clearly shows CP is weaker for sports.

### 7.2 Cloze Results

We ran the cloze task from with the help of probabilities calculated for both mixture and original model.

Model	Representation	CP		PMI		logp	
		Mean by line	Mean by event	Mean by line	Mean by event	Mean by line	Mean by event
Original	V+S+O	9.775	12.668	9.589	12.680	9.727	12.838
	V+S	9.535	11.909	<b>8.619</b>	10.645	9.224	11.539
	V+O	10.332	12.180	9.258	10.789	9.592	11.169
	V	9.708	10.791	9.582	10.846	<b>8.749</b>	9.599
Combined	V+S+O	9.250	11.840	9.199	11.961	8.996	11.678
	V+S	9.653	12.069	<b>8.314</b>	10.190	8.936	11.005
	V+O	10.275	11.961	9.610	11.145	9.315	10.708
	V	8.851	9.877	8.665	9.794	<b>8.586</b>	<b>9.415</b>

Table 5: Cloze results for travel stories

Model	Representation	CP		PMI		logp	
		Mean by line	Mean by event	Mean by line	Mean by event	Mean by line	Mean by event
Original	V+S+O	12.789	13.373	11.796	12.413	13.983	15.153
	V+S	13.351	14.555	12.810	13.905	13.320	14.207
	V+O	12.869	13.462	12.925	13.573	12.057	12.951
	V	11.050	11.870	9.259	9.755	9.477	10.299
Combined	V+S+O	13.515	14.22	12.664	13.75	14.274	15.196
	V+S	11.962	12.732	10.696	11.333	11.588	12.284
	V+O	12.488	13.088	11.853	12.333	10.758	11.373
	V	10.225	10.944	10.204	10.842	<b>9.246</b>	<b>9.818</b>

Table 6: Cloze results for sports stories

Verbs along with  $\log p$  does best at performing the cloze task irrespective of the domain and CP performs the worst.

One common inference from both the tasks is that CP does not perform better than  $\log p$  and Verbs in general has the highest expressive power, this could be because others get sparse since we tend to capture more information.

## 8 Future Work

There are many variants of the task to ascertain some of the inferences made in the paper. One is to set up a Human Intelligence Task on Mechanical Turk. This would actually validate our results. As seen in the (Chao et al., 2013) paper, the verbs alone representation did the best on MTurk and this matches to our inferences but we would need to validate it.

The other important task to do is to run the same procedure with more data, which is to get much cleaner data by using the patterns generated from AutoSlog(Riloff, 1999). Doing such high precision extraction of stories would help us in getting to know more insight about the representations.

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