Survey Report

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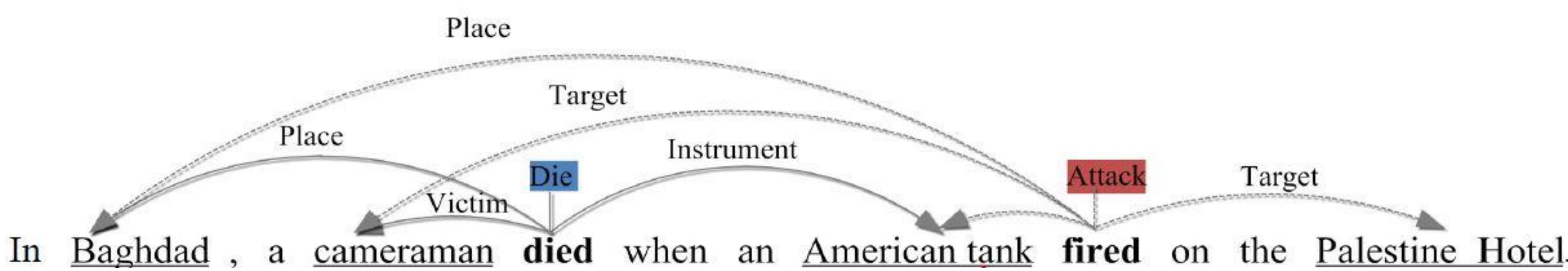
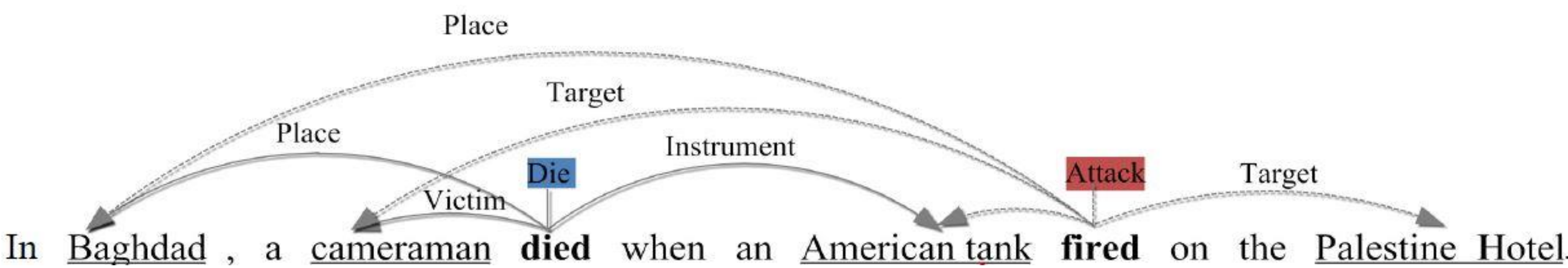
Some ACE terminology

- **Entity:** an object or a set of objects in one of the semantic categories.
- **Entity mention:** a reference to an entity.
- **Event mention:** a phrase or sentence within which an event is described.
- **Event trigger:** the main word that most clearly expresses an event occurrence.
- **Event mention arguments (roles):** the entity mentions that are involved in an event mention, and their relation to the event.



Definition of task

- **Goal:** identify and classify ***triggers*** (instances) of a class of events.
- **Other work:** identify and classify ***arguments*** (participants and attributes) of each event.



Evaluation Metric

- ***For trigger:*** event type, offsets match a reference trigger.
- ***For argument:*** event type, offsets match any of the reference argument mentions.
- ***For role:*** event type, offsets, and role match any of the reference argument mentions.

Data Set

- ID: LDC2006D06
- Number of documents: 599
- Component:

<table>
<tr><td colspan="3">Conversational Telephone Speech</td><td>39</td></tr>
<tr><td colspan="3">Usenet Newsgroups/Discussion Forum</td><td>49</td></tr>
<tr><td>Newswire</td><td>106</td><td>Broadcast News</td><td>226</td></tr>
<tr><td>Weblog</td><td>119</td><td>Broadcast Conversation</td><td>60</td></tr>
</table>

- Dev Set: randomly selected, 10 or 30
- Test Set: same 40 newswire articles

Definition of *Type*

Table 8 ACE05 Event Types and Subtypes

Types	Subtype
Life	Be-Born, Marry, Divorce, Injure, Die
Movement	Transport
Transaction	Transfer-Ownership, Transfer-Money
Business	Start-Org, Merge-Org, Declare-Bankruptcy, End-Org
Conflict	Attack, Demonstrate
Contact	Meet, Phone-Write
Personnel	Start-Position, End-Position, Nominate, Elect
Justice	Arrest-Jail, Release-Parole, Trial-Hearing, Charge-Indict, Sue, Convict, Sentence, Fine, Execute, Extradite, Acquit, Appeal, Pardon

Table 1 ACE05 Entity Types and Subtypes

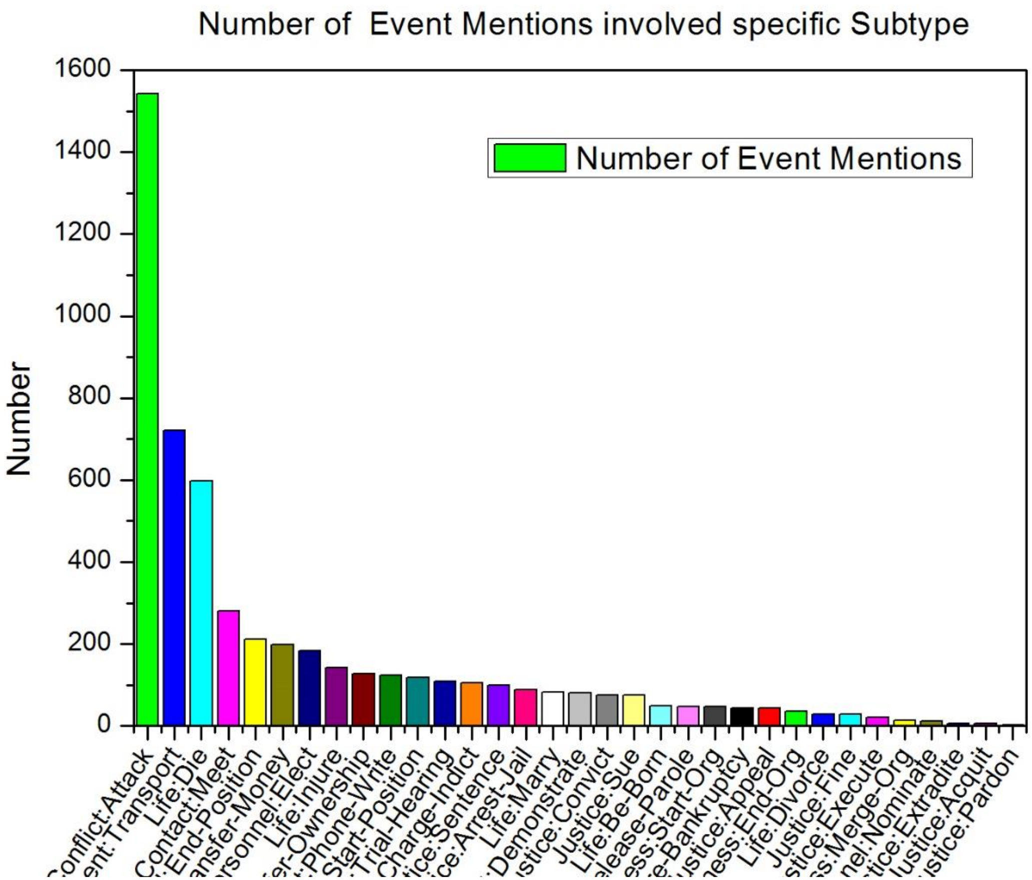
Type	Subtypes
FAC (Facility)	Airport, Building-Grounds, Path, Plant, Subarea-Facility
GPE (Geo-Political Entity[3])	Continent, County-or-District, GPE-Cluster, Nation, Population-Center, Special, State-or-Province
LOC (Location)	Address, Boundary, Celestial, Land-Region-Natural, Region-General, Region-International, Water-Body
ORG (Organization)	Commercial, Educational, Entertainment, Government, Media, Medical-Science, Non-Governmental, Religious, Sports
PER (Person)	Group, Indeterminate, Individual
VEH (Vehicle)	Air, Land, Subarea-Vehicle, Underspecified, Water
WEA (Weapon)	Biological, Blunt, Chemical, Exploding, Nuclear, Projectile, Sharp, Shooting, Underspecified

Definition of *Role*

Table 9 Argument roles allowable for events

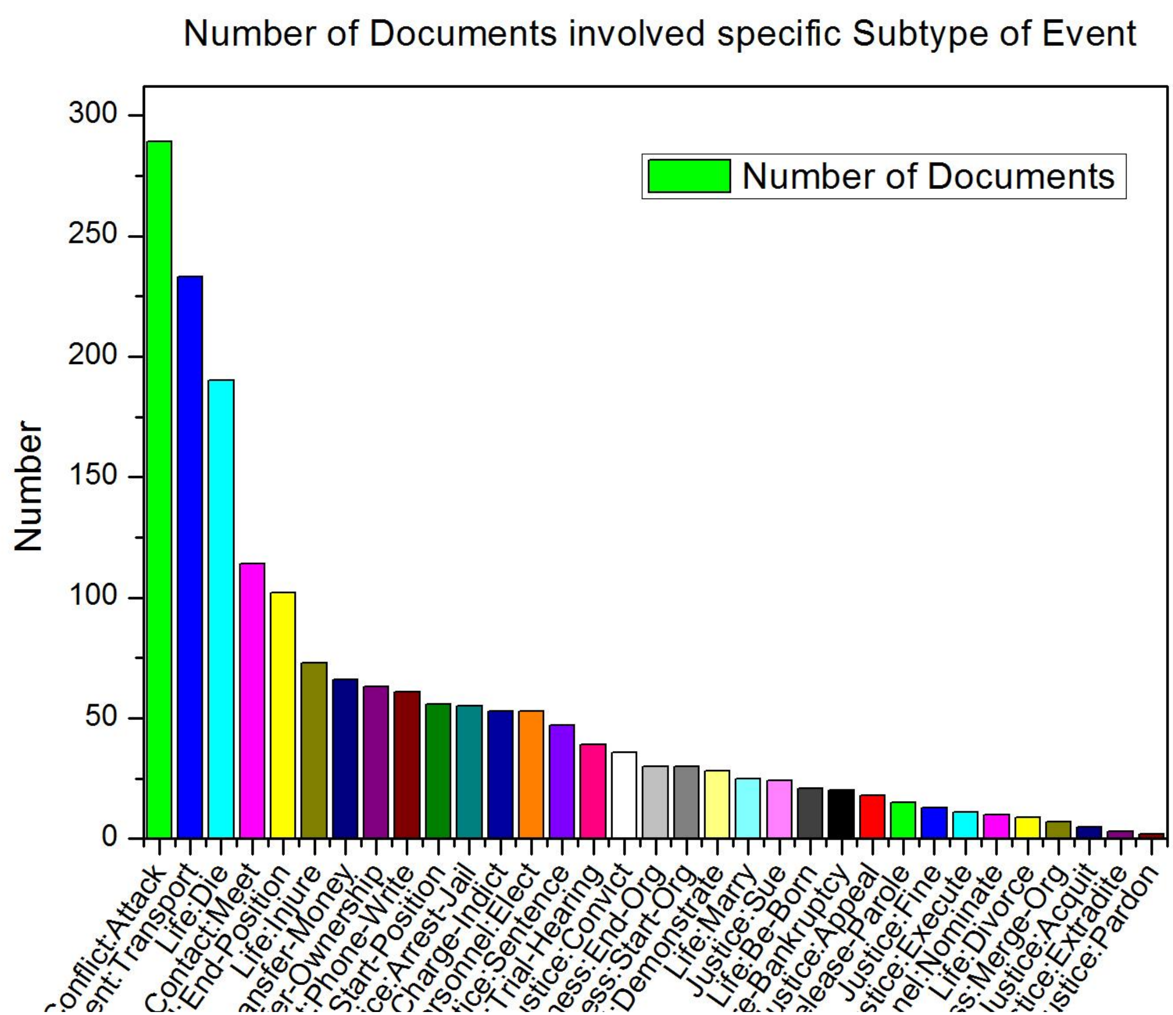
Allowable Event Roles		
Person	Place	Buyer
Seller	Beneficiary	Price
Artifact	Origin	Destination
Giver	Recipient	Money
Org	Agent	Victim
Instrument	Entity Entity	Attacker
Target	Defendant	Adjudicator
Prosecutor	Plaintiff	Crime
Position	Sentence	Vehicle
Time-After	Time-Before	Time-At-Beginning
Time-At-End	Time-Starting	Time-Ending
Time-Holds	Time-Within	

Analysis of Data Set



Number of event mentions in each sentence	Number of sentences	Percentage (%)
0	13945	80.310
1	2329	13.413
2	725	4.175
3	203	1.169
4	70	0.403
5	37	0.213
6	15	0.086
7	10	0.058
8	6	0.035
9	6	0.035
10	5	0.029
11	4	0.023
12	1	0.006
14	2	0.012
15	2	0.012
16	1	0.006
17	2	0.012
19	1	0.006
Total	17364	100.00

Analysis of Data Set



Current Methods

Category	Methods	Framework	Features	External Resources
Pipeline	Ralph Grishman (ACE 05) Jet (Baseline)	Pipeline	Lexical Features, Contextual Features	No
	Heng Ji (ACL 08) Cross-document Inference	Jet + Inference (Rules) [Consistency Learning]	within-document confidence, cross-document confidence	English TDT5
	Shasha Liao (ACL 10) Cross-event Inference	Jet + Inference (Classifier) [Collective Learning]	event type, event type ditribution , role ditribution	No
	Yu Hong (ACL 11) Cross-entity Inference	Pipeline with new features	event type, entity subtype, relation of entity subtype	Web
	Yubo Chen (ACL 15) Dynamic Multi-Pooling CNN	Pipeline (two stages) + One step[1] [semi-supervised Learning]	local: candidate words, context tokens global: context-word, position, event-type	NYT corpus
	Ofer Bronstein (ACL 15) Seed-Based Trigger Labeling	One step[1] (Just for trigger) [semi-supervised Learning]	4 binary features: Similarity with seeds in list.	WordNet
Joint	Qi Li (ACL 13) Joint structure	Joint[2] + One step[1]	25 local features, 8 global features	No

[1] One step: Identify and classify triggers and arguments in one step.

[2] Joint: Extract triggers and arguments together

Results

Methods	Trigger Identification(%)			Trigger Identification +Classification(%)			Argument Identification(%)			Argument Role(%)		
	P	R	F	P	R	F	P	R	F	P	R	F
05-Baseline (Jet)	N/A			67.6	53.5	59.7	46.5	37.1	41.3	41.0	32.8	36.5
08-Ji's Cross-document	N/A			60.2	76.4	67.3	55.7	39.5	46.2	51.3	36.4	42.6
10-Liao's Cross-event	N/A			68.7	68.9	68.8	50.9	49.7	50.3	45.1	44.1	44.6
11-Hong's Cross-entity	N/A			72.9*	64.3*	68.3*	53.4*	52.9*	53.1*	51.6*	45.5*	48.3*
13-Li's Joint structure	76.9	65.0	70.4	73.7 *	62.3*	67.5*/65.6	69.8 *	47.9*	56.8*	64.7 *	44.4*	52.7*/41.8
15-Chen's DMCNN	80.4	67.7	73.5	75.6	63.6	69.1	68.8	51.9	59.1	62.2	46.9	53.5
15-Bronstein's Seed-based	N/A			80.6	67.1	73.2	N/A			N/A		

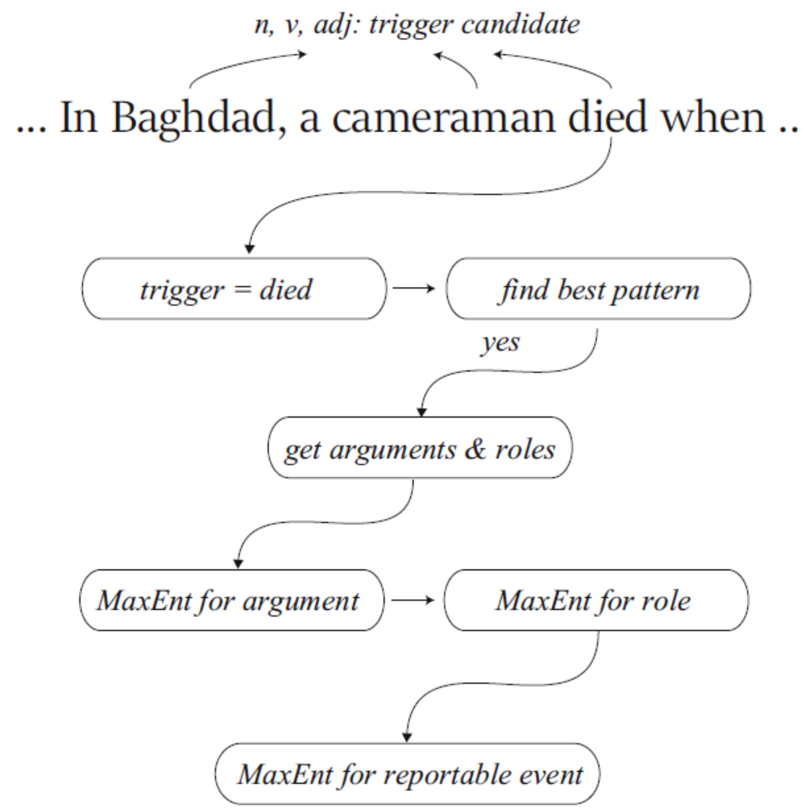
* indicate that the proposed system directly uses the entity labels provided by ACE.

Jet

Framework

The system combines pattern matching with statistical models.

- **Patterns for trigger identification:** sequences of constituent heads separating the trigger and arguments.
- **Argument Classifier:** to distinguish arguments of a potential trigger from non-arguments.
- **Role Classifier:** to classify arguments by argument role.
- **Reportable-Event Classifier (Trigger Classifier):** Given a potential trigger, an event type, and a set of arguments, to determine whether there is a reportable event mention.



(a) The flow chart of JET

Refining Event Extraction through Cross-document Inference

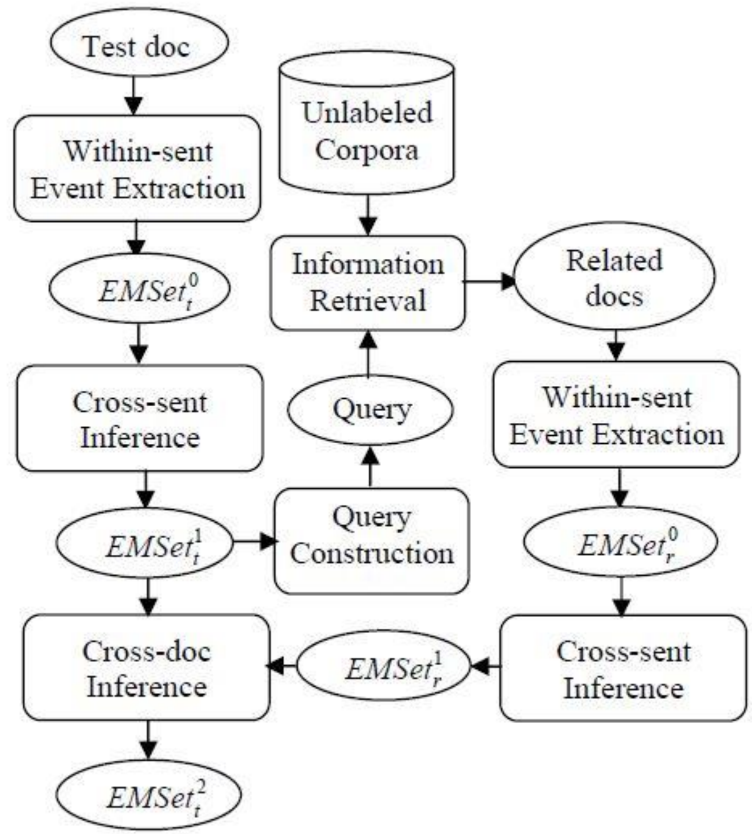
Motivation [Consistency Learning]

- **One Trigger Sense Per Cluster**
  - For a collection of topically-related documents, the distribution of triggers may be much more convergent.

- **One Argument Role Per Cluster**
  - In other words, each **entity** plays the same argument role, or no role, for events with the **same type** in a collection of related documents.

How to use motivation

- Using document-wide consistency to remove or adjust triggers and arguments.
- Using cluster-wide consistency to remove or adjust triggers and arguments.



Pros and Cons

- **Pros:**
  - Based on the hypothesis of "**One Sense Per Discourse**", author extends the scope of "discourse" from one single document to a cluster of **topically-related documents**.
  - Except for cluster-wide consistency, author also utilizes document-wide consistency.
- **Cons:**
  - Some specific cases will be removed or adjusted.

  Solution: fine-grained event type
  - Some unlabeled triggers or arguments will be wrong labeled. -- low precision

  Solution: Not just label all unlabeled mention.

Results

Methods	Trigger Identification(%)			Trigger Identification +Classification(%)			Argument Identification(%)			Argument Role(%)		
	P	R	F	P	R	F	P	R	F	P	R	F
05-Baseline (Jet)	N/A			67.6	53.5	59.7	46.5	37.1	41.3	41.0	32.8	36.5
08-Ji's Cross-document	**N/A**			**60.2**	**76.4**	**67.3**	**55.7**	**39.5**	**46.2**	**51.3**	**36.4**	**42.6**
10-Liao's Cross-event	N/A			68.7	68.9	68.8	50.9	49.7	50.3	45.1	44.1	44.6
11-Hong's Cross-entity	N/A			72.9*	64.3*	68.3*	53.4*	52.9*	53.1*	51.6*	45.5*	48.3*
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15-Bronstein's Seed-based	N/A			80.6	67.1	73.2	N/A			N/A		

* indicate that the proposed system directly uses the entity labels provided by ACE.

Using Document Level Cross-Event Inference to Improve Event Extraction

Motivation [Collective Learning]

If we first tag the easier cases, and use such knowledge to help tag the harder cases, we might get better overall performance.

- **Strong Consistency**
  - **Within a document**, if one instance of a word triggers an event, other instances of the same word will trigger events of the **same type**. 99.4%
  - Normally one entity, if it appears as an **argument** of multiple **events of the same type** in a single document, is assigned the **same role** each time. 97%
- **Strong Relationship**
  - When a event type appears in a document, some other certain event types appear in the same document.
  - When entities participate in event of certain type with a certain role, they will play limited role in limited event of different role.

How to use motivation

To take advantage of cross-event relationships, author trains two additional MaxEnt classifiers, then use these classifiers to infer additional events and event arguments.

Features of Trigger Classifier:

- The base form of the word
- An event type
- A binary indicator of whether this event type is present elsewhere in the document

- 1 & 2 reflect strong consistency of trigger
- 2 & 3 reflect strong relationship of trigger

Features of Argument (Role) Classifier:

- The event type we are trying to assign an argument/role to.
- One of the 32 other event types
- The role of this entity with respect to the other event type elsewhere in the document, or *null* if this entity is not an argument of that type of event

- 1 & 2 reflect strong consistency of role
- 2 & 3 reflect strong relationship of role

Pros and Cons

- **Pros:**
  - Author utilizes document level information and does not limit themselves to information about events of the same type. (compared with ji’s work)
  - Do not use external resources.
- **Cons:**
  - Some specific cases violate the strong consistency and relationship.

Results

Methods	Trigger Identification(%)			Trigger Identification +Classification(%)			Argument Identification(%)			Argument Role(%)		
	P	R	F	P	R	F	P	R	F	P	R	F
05-Baseline (Jet)	N/A			67.6	53.5	59.7	46.5	37.1	41.3	41.0	32.8	36.5
08-Ji's Cross-document	N/A			60.2	76.4	67.3	55.7	39.5	46.2	51.3	36.4	42.6
10-Liao's Cross-event	**N/A**			**68.7**	**68.9**	**68.8**	**50.9**	**49.7**	**50.3**	**45.1**	**44.1**	**44.6**
11-Hong's Cross-entity	N/A			72.9*	64.3*	68.3*	53.4*	52.9*	53.1*	51.6*	45.5*	48.3*
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15-Bronstein's Seed-based	N/A			80.6	67.1	73.2	N/A			N/A		

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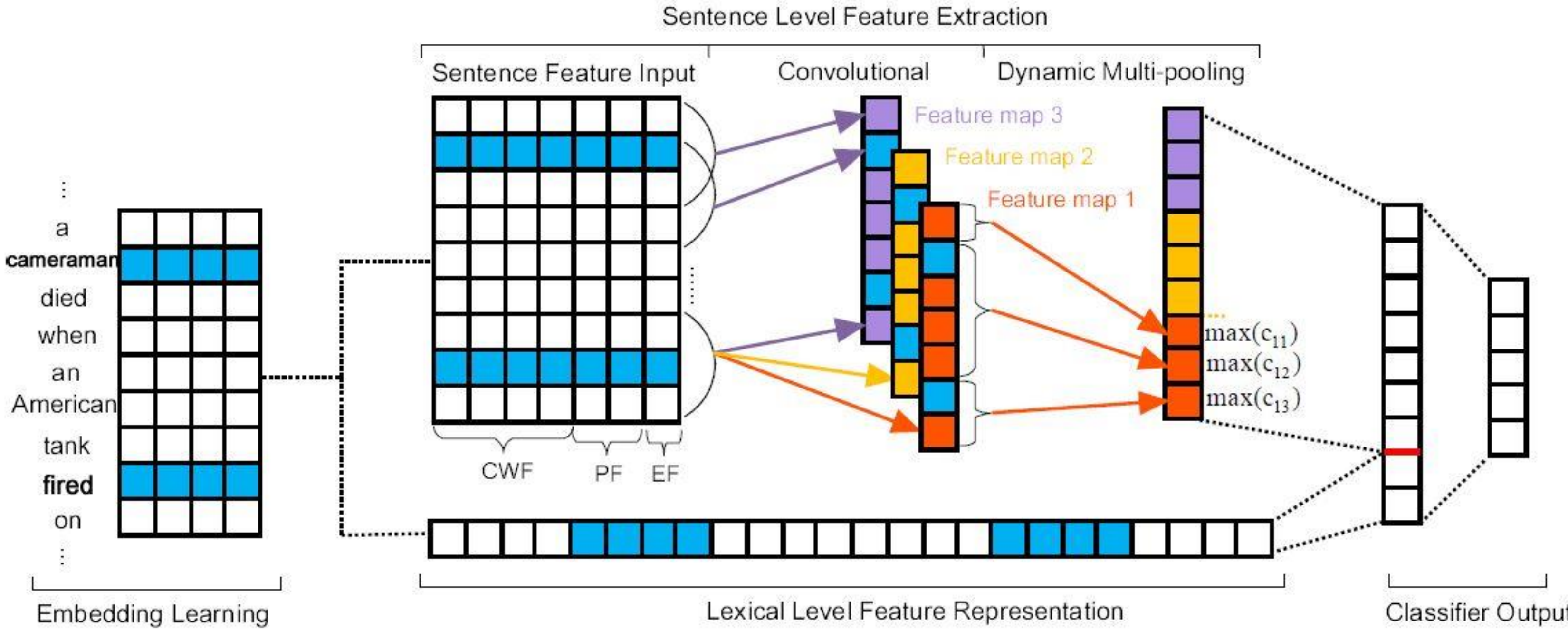
Event Extraction via Dynamic Multi-Pooling Convolutional Neural Network

Motivation [semi-supervised Learning]

- Traditional Methods utilize a set of elaborately designed features which lack generalization and take a large amount of human effort.
- This paper introduces a word-representation model to capture meaningful semantic regularities for words (lexical features) and adopt a framework based on a convolutional neural network (CNN) to capture sentence-level clues (Contextual features).

Architecture of argument classification



Architecture of NLP from Scratch

A unified neural network architecture and learning algorithm that can be applied to various natural language processing tasks including: part-of-speech tagging, chunking, named entity recognition, and semantic role labeling.

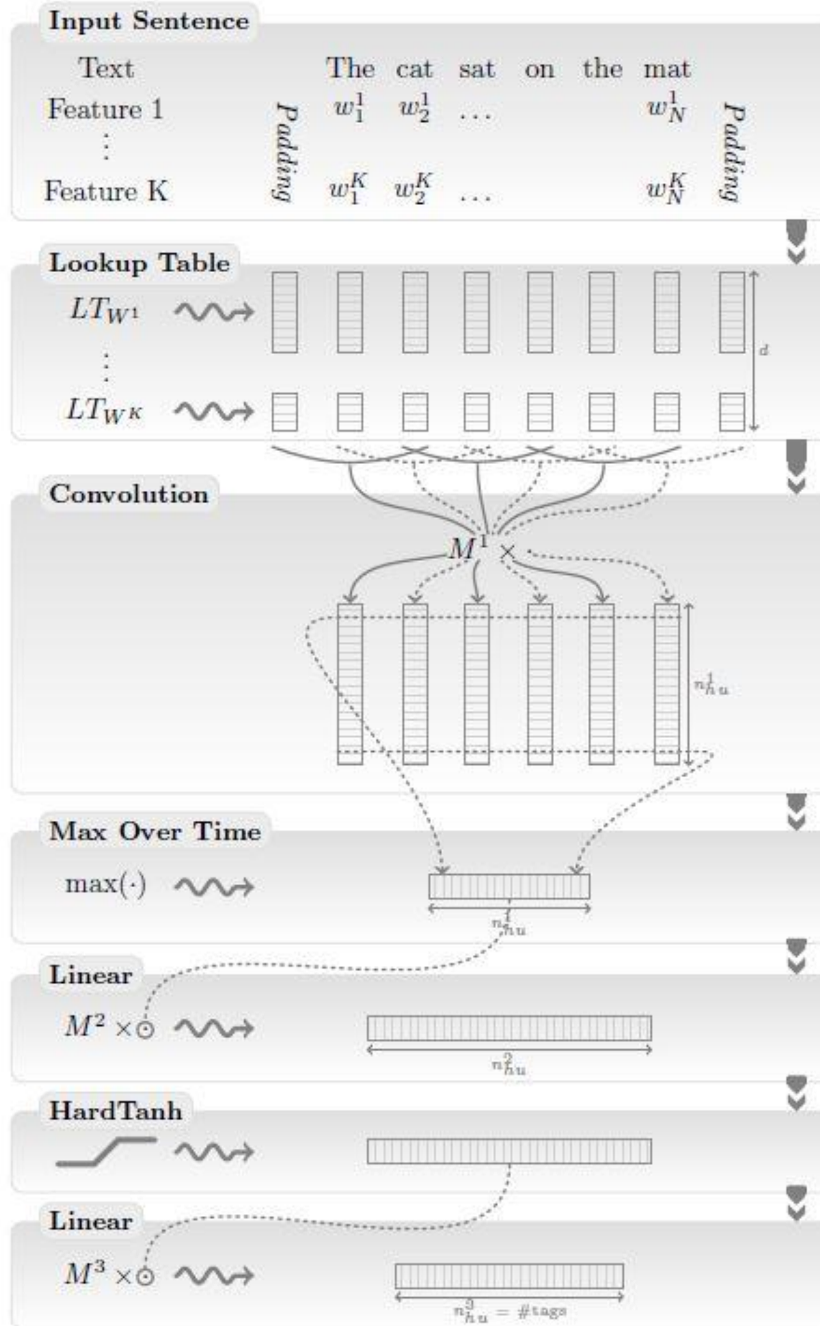
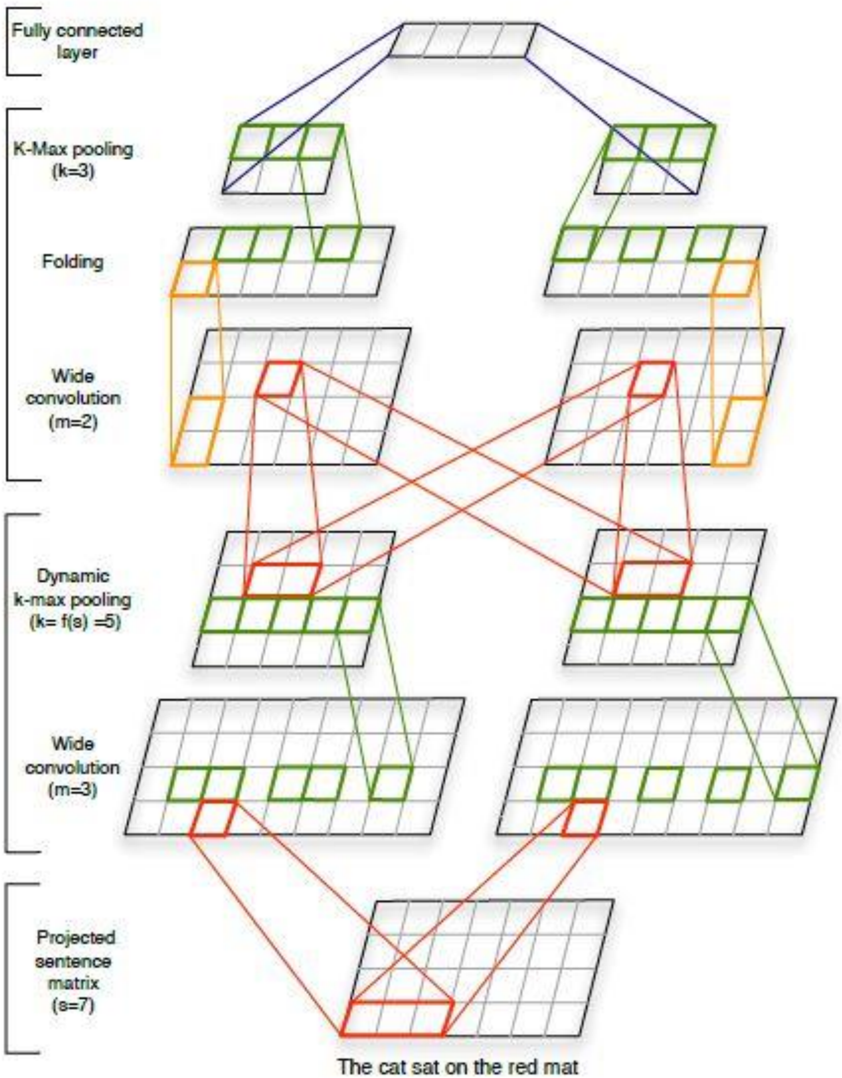


Figure 2: Sentence approach network.

A CNN for Modelling Sentences



The network uses Dynamic k-Max Pooling, a global pooling operation over linear sequences.

Pros and Cons

- **Pros:**
  - This paper utilizes new method to generate useful features which are simple and intuitive.
  - This paper can identify and classify triggers and arguments in one step.
- **Cons:**
  - Some consistency and relationship can be used to improve the system performance.
  - New features may be used to improve the performance.

Results

Methods	Trigger Identification(%)			Trigger Identification +Classification(%)			Argument Identification(%)			Argument Role(%)		
	P	R	F	P	R	F	P	R	F	P	R	F
05-Baseline (Jet)	N/A			67.6	53.5	59.7	46.5	37.1	41.3	41.0	32.8	36.5
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15-Bronstein's Seed-based	N/A			80.6	67.1	73.2	N/A			N/A		

* indicate that the proposed system directly uses the entity labels provided by ACE.

Seed-Based Event Trigger Labeling: How far can event descriptions get us?

Framework [semi-supervised Learning]

- Given the guideline for a new event type, this method collects these triggers into a list of seeds. (Per event type has 4.2 seeds in list on average, compared to 46 distinct trigger terms in the training corpus)
- Then, this method assesses each test text token similarity to the seed in list based on WordNet and lemma.

Cons:

- This method are highly dependent on WordNet.
- Larger training didn’t improve results, possibly due to the small number of features.

Results

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15-Bronstein's Seed-based	**N/A**			**80.6**	**67.1**	**73.2**	**N/A**			**N/A**		

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Review

- ***Heng Ji (ACL 08):*** This paper employs a similar approach to propagate consistent event arguments across sentences and documents. **[Consistency Learning]**
- ***Shasha Liao (ACL 10):*** This paper finds strong correlations among event types and a strong relationship between the roles in a document. They use document level cross-event information based on what they find to improve the performance. **[Collective Learning]**
- ***Yubo Chen (ACL 15):*** This paper utilizes word embedding to automatically extract lexical-level features and utilize word embedding as well as dynamic multi-pooling CNN to extract sentence-level features. **[semi-supervised Learning]**
- ***Ofer Bronstein (ACL 15):*** This paper uses annotation guidelines and WordNet to construct similarity-based classifier which is used to identify and classify trigger. **[semi-supervised Learning]**

Discussion

Challenge

- Training data is insufficient and heterogeneous.
  - Insufficient data cannot provide ample evidence to handle all cases in test set. e.g., Hong’s trigger F-score is low.
  - Across a heterogeneous document corpus, a particular verb can sometimes be trigger and sometimes not, and can represent different event types. e.g., conflict table in Liao’s method.
- Good features are difficult to find
  - E.g., entity subtype consistency is useful to distinguish role of argument.

Solution

- For training data
  - Using external resources: web and other corpus
    - Fine-grained: subtype of entity
    - Resolve ambiguities
  - Using good representation: embedding
    - Not sparsity
    - capture the semantics and similarity of the words
- *For* good features
  - We can analyse dev set and find new patterns.

What we can do?

- We can use seed-based method to improve trigger F1 score in previous method.
- We can cluster the embeddings and find useful information.
- We can add new features to DMCNN, e.g., subtype of entity, binary indicator of distribution of event type.

End

Using Cross-Entity Inference to Improve Event Extraction

Motivation

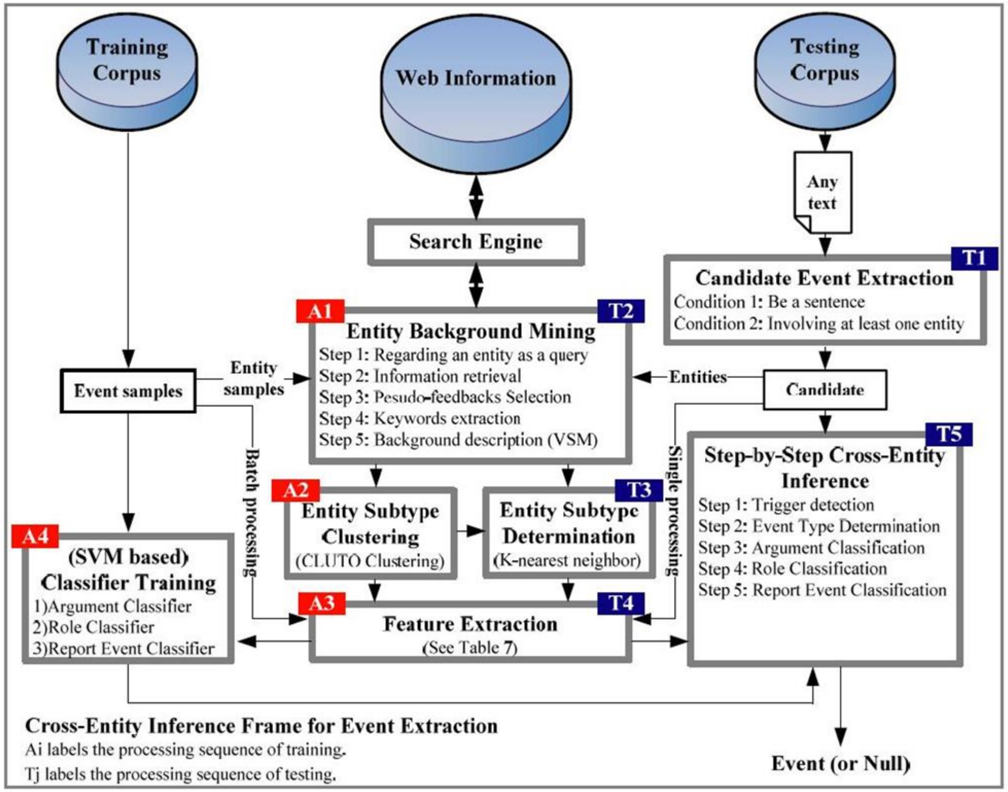
- **Strong Entity Consistency:**
  - If one entity mention appears in a type of event, other entity mentions of the same type will appear in similar events, and even use the same word to trigger the events.
- **Strong Role Consistency:**
  - Entities of the same type normally play the same role, especially in the event mentions of the same type.

How to use motivation

1. Divide the ACE entity type into more cohesive subtype.
2. Construct three SVM classifier based on entity subtype and event type.

Argument Classifier
Feature 1: an event type (an event-mention domain)
Feature 2: an entity subtype
Feature 3: entity-subtype co-occurrence in domain
Feature 4: distance to trigger
Feature 5: distances to other arguments
Feature 6: co-occurrence with trigger in clause
Role Classifier
Feature 1 and *Feature 2*
Feature 7: entity-subtypes of arguments
Reportable-Event Classifier
Feature 1
Feature 8: confidence coefficient of trigger in domain
Feature 9: confidence coefficient of role in domain

Table 7: Features selected for SVM-based cross-entity classifiers



Pros and Cons

- **Pros:**
  - This paper found that the entities within a sentence, as the most important local information, actually contain sufficient clues for event detection.
  - The features of classifier are simple and intuitive.
- **Cons:**
  - This paper instead directly uses the entity labels provided by ACE. The results will decrease if uses entity labels extracted by jet system.
  - Something can be done to improve the identification and classification of trigger,

Results

Methods	Trigger Identification(%)			Trigger Identification +Classification(%)			Argument Identification(%)			Argument Role(%)		
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15-Bronstein's Seed-based	N/A			80.6	67.1	73.2	N/A			N/A		

* indicate that the proposed system directly uses the entity labels provided by ACE.

Joint Event Extraction via Structured Prediction with Global Features

Motivation

- As a common drawback of the staged architecture, errors in upstream component are often compounded and propagated to the downstream classifiers.
- By contrast, this paper proposes a joint framework based on structured prediction which extracts triggers and arguments together so that the local predictions can be mutually improved.

Symbol Description

- **Instance:**

$$x = \langle (x_1, x_2, ..., x_s), \mathcal{E} \rangle$$

- **Configuration:**

$$y = (t_1, a_{1,1}, \ldots, a_{1,m}, \ \ldots, \ t_s, a_{s,1}, \ldots, a_{s,m})$$

- **Example:**

$$x = \langle (Jobs, \overbrace{founded}^{x_2}, Apple), \overbrace{\{Jobs_{\text{PER}}, Apple_{\text{ORG}}\}}^{\mathcal{E}} \rangle$$
$$y = (\perp, \perp, \perp, \underbrace{Start\_Org}_{t_2}, \underbrace{Agent, \ Org}_{\text{args for } founded}, \perp, \perp, \perp)$$

Architecture of joint system

- **Goal function:** $z = \operatorname*{argmax}_{y' \in \mathcal{Y}(x)} \mathbf{w} \cdot \mathbf{f}(x, y')$
- **Method:** Beam-search with early-update strategy
- **Algorithm:**

Input: Training set $\mathcal{D} = \{(x^{(j)}, y^{(j)})\}_{i=1}^{n}$,
maximum iteration number T

Output: Model parameters $\mathbf{w}$

```
Initialization: Set w = 0;
for t ← 1...T do
    foreach (x, y) ∈ D do
        z ← beamSearch (x, y, w)
        if z ≠ y then
            w ← w + f(x, y_[1:|z|]) − f(x, z)
```

Figure 2: Perceptron training with beam-search (Huang et al., 2012). Here $y_{[1:i]}$ denotes the prefix of y that has length i, e.g., $y_{[1:3]} = (y_1, y_2, y_3)$.

Process of Labeling -- BeamSearch

Input: Instance $x = \langle (x_1, x_2, ..., x_s), \mathcal{E} \rangle$ and the oracle output y if for training.

K: Beam size.

$\mathcal{L} \cup \{\perp\}$: trigger label alphabet.

$\mathcal{R} \cup \{\perp\}$: argument label alphabet.

Output: 1-best prediction z for x

1 Set beam $\mathcal{B} \leftarrow [\epsilon]$ /*empty configuration*/
2 **for** $i \leftarrow 1...s$ **do**
3   $buf \leftarrow \{z' \circ l \mid z' \in \mathcal{B}, l \in \mathcal{L} \cup \{\perp\}\}$
    $\mathcal{B} \leftarrow$K-best(buf)
4   **if** $y_{[1:g(i)]} \notin \mathcal{B}$ **then**
5   return $\mathcal{B}[0]$ /*for early-update*/
6   **for** $e_k \in \mathcal{E}$ **do** /*search for arguments*/
7     $buf \leftarrow \emptyset$
8   **for** $z' \in \mathcal{B}$ **do**
9       $buf \leftarrow buf \cup \{z' \circ \perp\}$
10   **if** $z'_{g(i)} \neq \perp$ **then** /*x_i is a trigger*/
11         $buf \leftarrow buf \cup \{z' \circ r \mid r \in \mathcal{R}\}$
12     $\mathcal{B} \leftarrow$K-best(buf)
13   **if** $y_{[1:h(i,k)]} \notin \mathcal{B}$ **then**
14   return $\mathcal{B}[0]$ /*for early-update*/
15 return $\mathcal{B}[0]$

Figure 4: Decoding algorithm for event extraction. $z \circ l$ means appending label l to the end of z. During test, lines 4-5 & 13-14 are omitted.

Cons:

- As in Hong's method, gold-standard argument candidates play a very important role in argument identification and classification.
- If previous method utilize gold-standard entities, they may have impressive results.

Methods	Trigger F_1	Arg F_1
Ji and Grishman (2008) cross-doc Inference	67.3	42.6
Ji and Grishman (2008) sentence-level	59.7	36.6
MaxEnt classifiers	64.7 (↓1.2)	33.7 (↓10.2)
Joint w/ local	63.7 (↓2.0)	35.8 (↓10.7)
Joint w/ local + global	**65.6** (↓**1.9**)	**41.8** (↓10.9)

Table 7: Overall performance (%) with predicted entities, timex, and values. ↓ indicates the performance drop from experiments with gold-standard argument candidates (see Table 6).

Review

- ***Jet:*** The system combines pattern matching with statistical models.
- ***Heng Ji (ACL 08):*** This paper employs a similar approach to propagate consistent event arguments across sentences and documents.
- ***Shasha Liao (ACL 10):*** This paper finds strong correlations among event types and a strong relationship between the roles in a document. They use document level cross-event information based on what they find to improve the performance.
- ***Yu Hong (ACL 11):*** This paper finds the entity consistency in event type and role, so they regard entity subtype consistency as key feature to predict event mentions.
- ***Qi Li (ACL 13):*** This paper proposes a joint framework based on structured prediction which extracts triggers and arguments together so that the local predictions can be mutually improved.
- ***Yubo Chen (ACL 15):*** This paper utilizes word embedding to automatically extract lexical-level features and utilize word embedding as well as dynamic multi-pooling CNN to extract sentence-level features.
- ***Ofer Bronstein (ACL 15):*** This paper uses annotation guidelines and WordNet to construct similarity-based classifier which is used to identify and classify trigger

Results

Methods	Trigger Identification(%)			Trigger Identification +Classification(%)			Argument Identification(%)			Argument Role(%)		
	P	R	F	P	R	F	P	R	F	P	R	F
05-Baseline (Jet)	N/A			67.6	53.5	59.7	46.5	37.1	41.3	41.0	32.8	36.5
08-Ji's Cross-document	N/A			60.2	76.4	67.3	55.7	39.5	46.2	51.3	36.4	42.6
10-Liao's Cross-event	N/A			68.7	68.9	68.8	50.9	49.7	50.3	45.1	44.1	44.6
11-Hong's Cross-entity	N/A			72.9*	64.3*	68.3*	53.4*	52.9*	53.1*	51.6*	45.5*	48.3*
13-Li's Joint structure	**76.9**	**65.0**	**70.4**	**73.7 ***	**62.3***	**67.5*/65.6**	**69.8 ***	**47.9***	**56.8***	**64.7 ***	**44.4***	**52.7*/41.8**
15-Chen's DMCNN	80.4	67.7	73.5	75.6	63.6	69.1	68.8	51.9	59.1	62.2	46.9	53.5
15-Bronstein's Seed-based	N/A			80.6	67.1	73.2	N/A			N/A		

* indicate that the proposed system directly uses the entity labels provided by ACE.

Algorithm Category

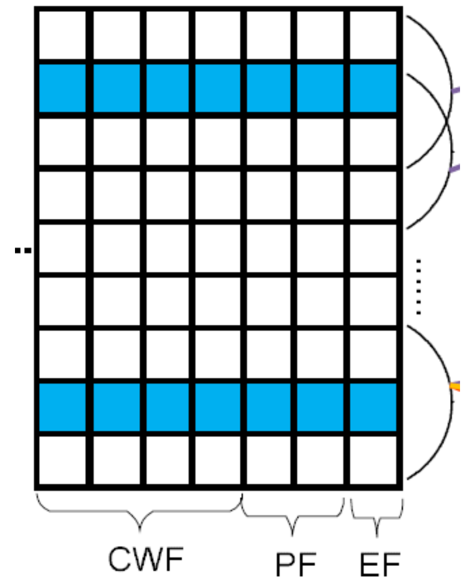
Category	Methods	Framework	Features	External Resources
Pipeline	Ralph Grishman (ACE 05) Jet (Baseline)	Pipeline	Lexical Features, Contextual Features	No
	Heng Ji (ACL 08) Cross-document Inference	Jet + Inference (Rules) [Consistency Learning]	within-document confidence, cross-document confidence	English TDT5
	Shasha Liao (ACL 10) Cross-event Inference	Jet + Inference (Classifier) [Collective Learning]	event type, event type ditribution , role ditribution	No
	Yu Hong (ACL 11) Cross-entity Inference	Pipeline with new features	event type, entity subtype, relation of entity subtype	Web
	Yubo Chen (ACL 15) Dynamic Multi-Pooling CNN	Pipeline (two stages) + One step[1] [semi-supervised Learning]	local: candidate words, context tokens global: context-word, position, event-type	NYT corpus
	Ofer Bronstein (ACL 15) Seed-Based Trigger Labeling	One step[1] (Just for trigger)	4 binary features: Similarity with seeds in list.	WordNet
Joint	Qi Li (ACL 13) Joint structure	Joint[2] + One step[1]	25 local features, 8 global features	No

New Features

Argument Classifier
Feature 1: an event type (an event-mention domain)
Feature 2: an entity subtype
Feature 3: entity-subtype co-occurrence in domain
Feature 4: distance to trigger
Feature 5: distances to other arguments
Feature 6: co-occurrence with trigger in clause
Role Classifier
Feature 1 and ***Feature 2***
Feature 7: entity-subtypes of arguments
Reportable-Event Classifier
Feature 1
Feature 8: confidence coefficient of trigger in domain
Feature 9: confidence coefficient of role in domain

Table 7: Features selected for SVM-based cross-entity classifiers

Features in Yu Hong's method



Features for argument classification in DMCNN

```
1P: entities          DUAL: entities
    values                  values
    events                  events
    relations               relations
       |                        |
       |                        |
       |__________?_____________|
                  |
                  |
                  |
                  V
            ADJ: entities
                 values
                 events
                 relations
                  |
                  |
                  |
                  V
            NORM: TIMEX2 normalization
                  (English only)
```

English

	words				files			
	1P	DUAL	ADJ	NORM	1P	DUAL	ADJ	NORM
NW	60658	57807	33459	48399	128	124	81	106
BN	59239	58144	52444	55967	239	234	217	226
BC	46612	46110	33874	40415	68	67	52	60
WL	45210	43648	35529	37897	127	122	114	119
UN	45161	44473	26371	37366	58	57	37	49
CTS	47003	47003	34868	39845	46	46	34	39
Total	303833	297185	216545	259889	666	650	535	599

Training data files for all languages are dually annotated for all tasks by two annotators working independently. The first pass (complete) annotation is called 1P; the independent dual first pass (complete) annotation is called DUAL. For both 1P and DUAL, a single annotator completes all tasks (entities, values, relations & events) for a file. Files are assigned via an automated Annotation Workflow System (AWS), and file assignment is double-blind.

Discrepancies between the 1P and DUAL version of each file are then adjudicated by a senior annotator or team leader, resulting in a high-quality gold standard file. The gold standard adjudicated file is known as ADJ. After adjudication, TIMEX2 values are normalized for English only. This task is known as NORM.