Coarse-grained IE:Event Extraction

How To Predict The Stock Based On News Events

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2. Representation
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4. Embedding
5. Application(Stock Prediction)

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Example news [Ding et al., 2014]

Steve Jobs Death: Apple Stock (AAPL) Dips - ABC News
abcnews.go.com › Money
Oct 6, 2011 - Shares of **Apple** Inc. fell as trading began in New York on Thursday morning, the day after former CEO Steve Jobs passed away.

Google's stock falls after grim earnings come out early - Oct. 18, 2012
money.cnn.com/2012/10/18/technology/**google**-earnings/
Oct 18, 2012 - **Google's** third-quarter earnings results missed analysts' estimates on both sales and profit, in a report that was accidentally released early.

Figure: Example news for Apple Inc. and Google Inc.

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The two news are discribed below:

1. Shares of Apple Inc. fell as trading began in New York on Thursday morning, the day after its former CEO Steve Jobs passed away.
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Unstructured Features

Shallow Features:

1. Bags of words
2. Noun phrases
3. Named entities

eg : "Apple has sued Samsung Electronics for copying 'the look and feel' of its iPad tablet and iPhone smartphone."

Bags of words feature : "Apple", "sued", "Samsung", "Electronics","copying",. . .

Shortcoming:

1. Such unstructured representation can not indicate the actor(subject) and object of the event.
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Structured Features

Representation	$E = (O_1, P, O_2, T)$
O_1	Actor(Subject) of event
P	Action(Predicate) of event
O_2	Object of event
T	Timestamp of event

eg : Sep 3, 2013, - Microsoft agrees to buy Nokia's mobile phone business for $7.2 billion.

Structured Representation:

- Actor =Microsoft
- Action = buy
- Object = Nokia's mobile phone business
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Event Extraction

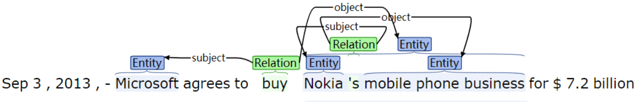

Figure: Event Extraction With Stanford Open IE tool

Candidate Tuples Of The Event:

1. (Microsoft, buy, Nokia's mobile phone business, Sep 3 2013)
2. (Nokia, 's, mobile phone business, Sep 3 2013)

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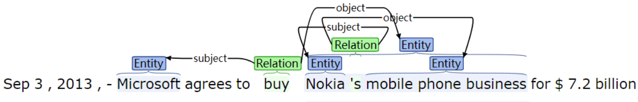

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Filter Out Bad Event Tuples

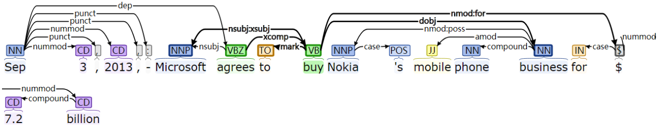

Figure: Filter Out Bad Tuples With tools like Dependency Parsing

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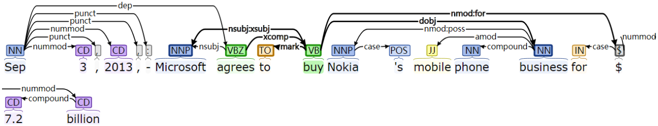

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Event Generalization

Example : **"Instant view: Private sector adds 114,000 jobs in July."**

$$(private\ sector, adds, 114\ 000\ jobs)$$

Event Generalization:

1. 'adds' and 'jobs' can be 'add' and 'job' respectively using some Stemmer tools
2. 'add' belongs to 'multiply' class With the help of VerbNet

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Why Embedding?

Two events $(Nvidia\ fourth\ quarter\ results, miss, views)$ and $(Delta\ profit, didn't\ reach, estimates)$ has different structured representation, which increases the data sparsity

With Embedding these two things can have the similar vector. [Ding et al., 2015]

Embedding With Neural Tensor Network

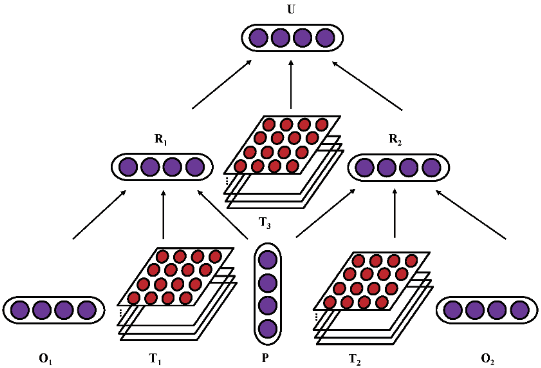

Figure: Neural tensor network for event embeddings

$$R_1 = f(O_1^T T_1^{[1:k]} P + W \begin{bmatrix} O_1 \\ P \end{bmatrix} + b_1) \text{ (the same with } R_2 \text{ and } U)$$

Neural Tensor Network Training

Training loss:

$$loss(E, E^{\tau}) = \max(0, 1 - f(E) + f(E^{\tau})) + \lambda \|\Phi\|_2^2$$

where $E = (O_1, P, O_2)$ and $E^{\tau} = (O_1^{\tau}, P, O_2)$

Algorithm 1: Event Embedding Training Process

Input: $\mathcal{E} = (E_1, E_2, \cdots, E_n)$ a set of event tuples; the model $EELM$

Output: updated model $EELM'$

random replace the event argument and got the corrupted event tuple

$\mathcal{E}^r \leftarrow (E_1^r, E_2^r, \cdots, E_n^r)$

while $\mathcal{E} \neq [\,]$ **do**

  $loss \leftarrow max\,(0\,,\,1 - f(E_i) + f(E_i^r) + \lambda \|\boldsymbol{\Phi}\|_2^2$

  if $loss > 0$ **then**

    $Update(\boldsymbol{\Phi})$

  else

    $\mathcal{E} \leftarrow \mathcal{E}/\{E_i\}$

return $EELM$

Embeddding With External Knowledge

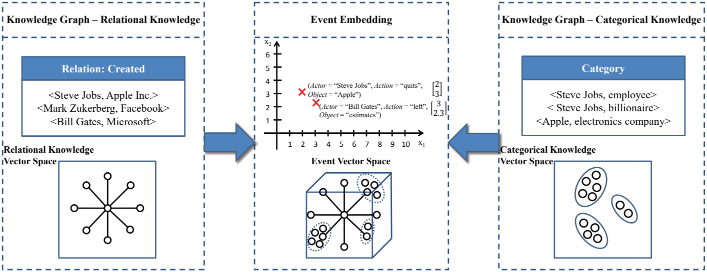

Figure: Incorporating knowledge graph into the learning process for event embeddings [Ding et al., 2016]

Trainging With External Knowledge

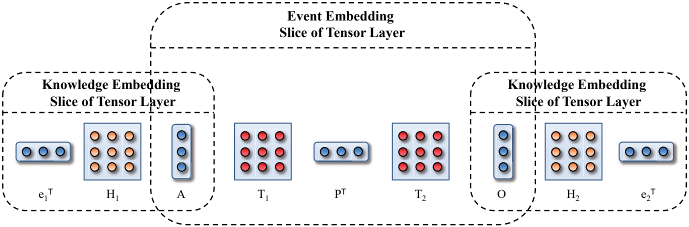

Figure: Architecture of the joint embedding model (only showing the tensor layer)

$$L = \alpha L_\epsilon + (1-\alpha) L_\kappa$$
$$L_\epsilon = loss(E, E^\tau) = \max(0, 1 - f(E) + f(E^\tau)) + \lambda \|\Phi\|_2^2$$
$$L_\kappa = \sum_{i=1}^{N} \sum_{m=1}^{M} \max(0, 1 - g(T^{(i)}) + g(T_c^{(i)})) + \lambda \|\Omega\|_2^2$$
where $E = (O_1, P, O_2)$, $T^{(i)} = (e_1^{(i)}, R, e_2^{(i)})$

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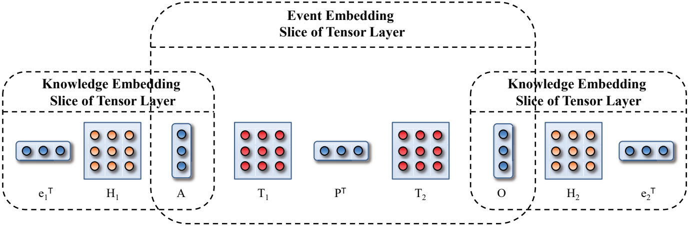

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Prediction Model

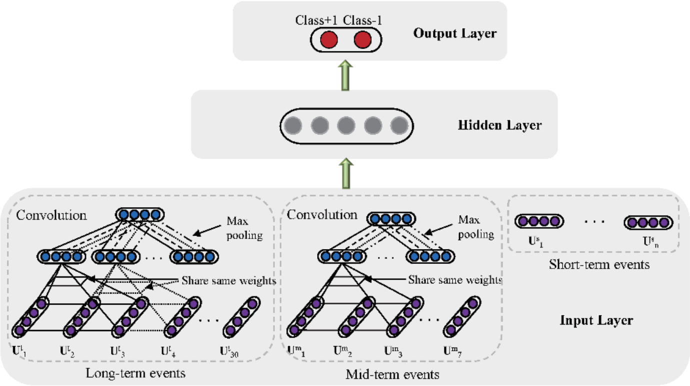
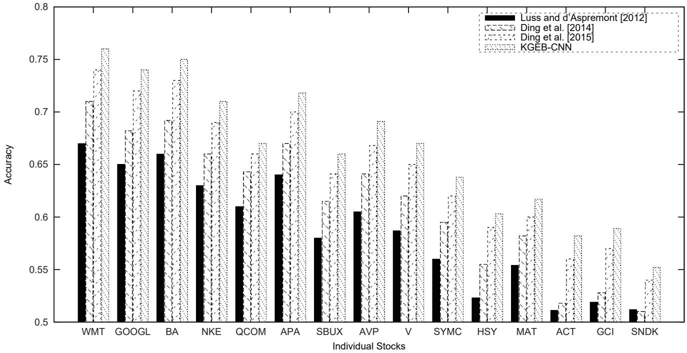


Figure: Architecture of the prediction model based on a deep convolutional neural network.

Table 3: Experimental results on index prediction.

	Acc	MCC
Luss and d'Aspremont (2012)	56.38%	0.0711
Ding et al. (2014)	58.83%	0.1623
WB-CNN	60.57%	0.1986
Ding et al. (2015)	64.21%	0.4035
KGEB-CNN	**66.93%**	**0.5072**



Thank You!

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