

Deep Learning for Event-Driven Stock Prediction



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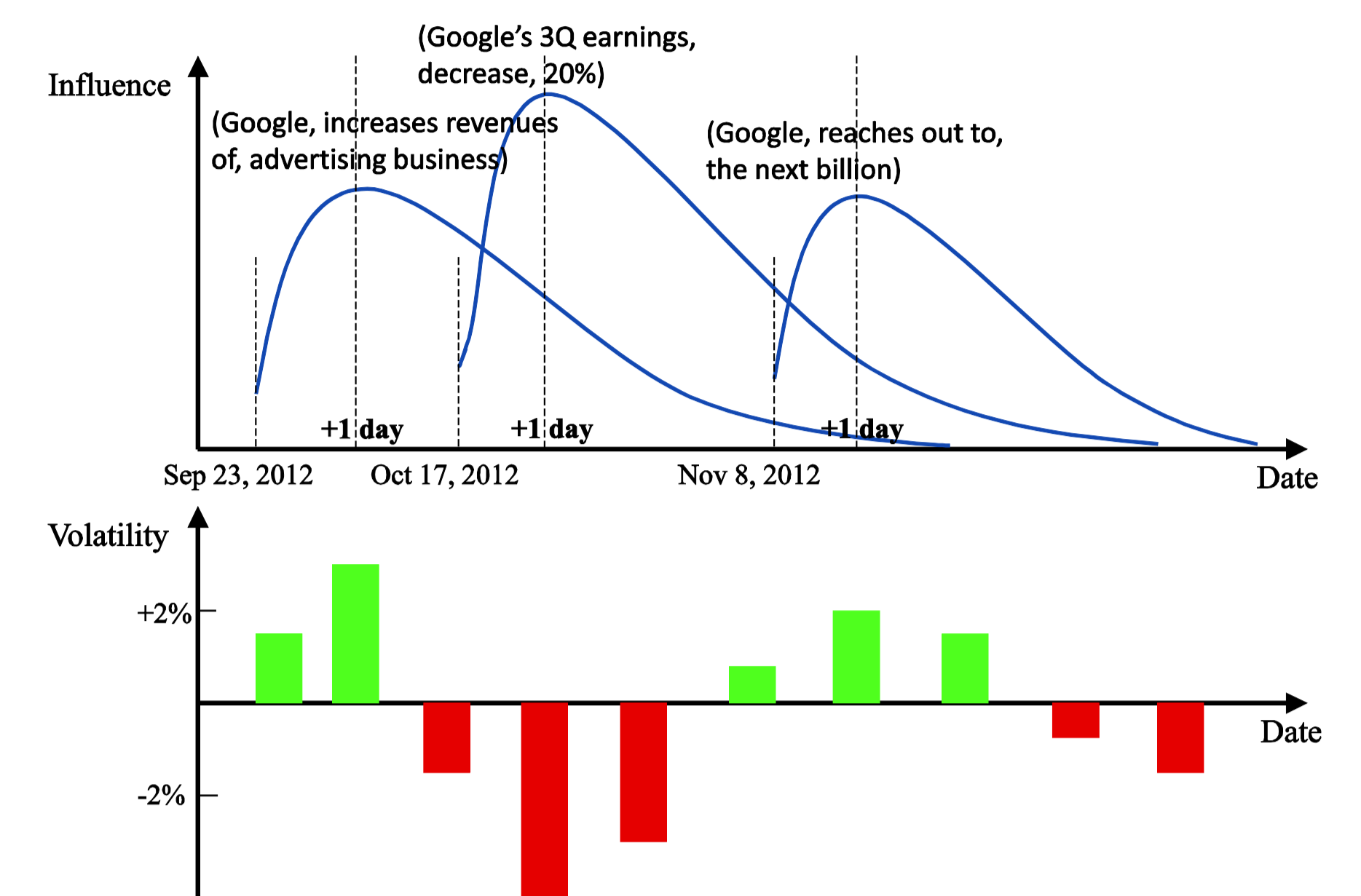
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Motivation

- Event sparsity
 - One disadvantage of structured representations of events is that they lead to increased sparsity, which potentially limits the predictive power
- Modeling long-term effect of events
 - Research shows diminishing effects of reported events on stock market volatility

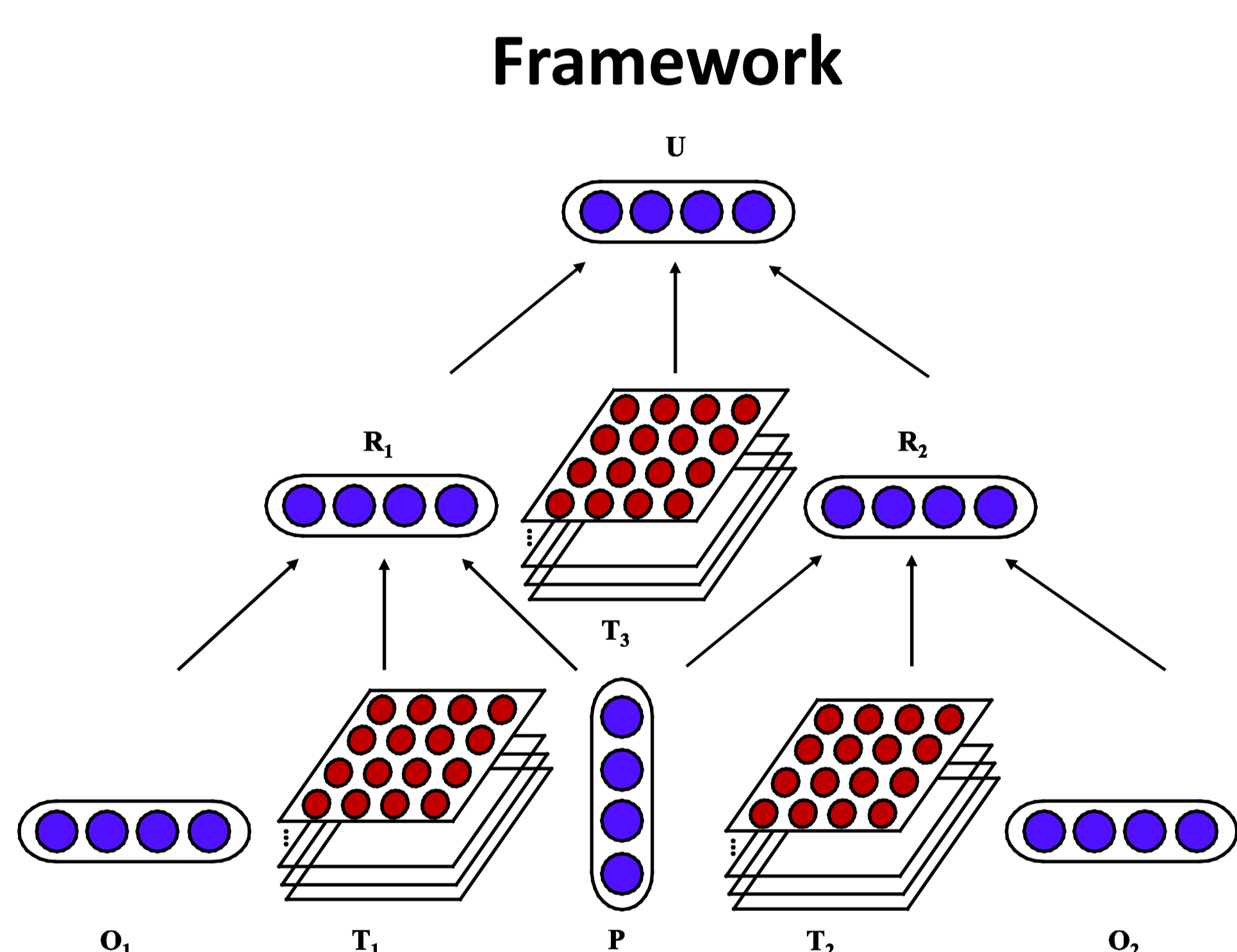


Neural Tensor Network for Learning Event Embeddings

Event Representation

$E = (O_1, P, O_2, T)$, where P is the action, O_1 is the actor, O_2 is the object and T is the timestamp (T is mainly used for aligning stock data with news data). For example, the event “Sep 3, 2013 - Microsoft agrees to buy Nokia’s mobile phone business for \$7.2 billion.” is modeled as: (Actor = *Microsoft*, Action = *buy*, Object = *Nokia’s mobile phone business*, Time = *Sep 3, 2013*)

Event Embedding



Training

Loss function: $loss(E, E^r) = \max(0, 1 - f(E) + f(E^r)) + \lambda \|\Phi\|_2^2$

Algorithm 1: Event Embedding Training Process

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

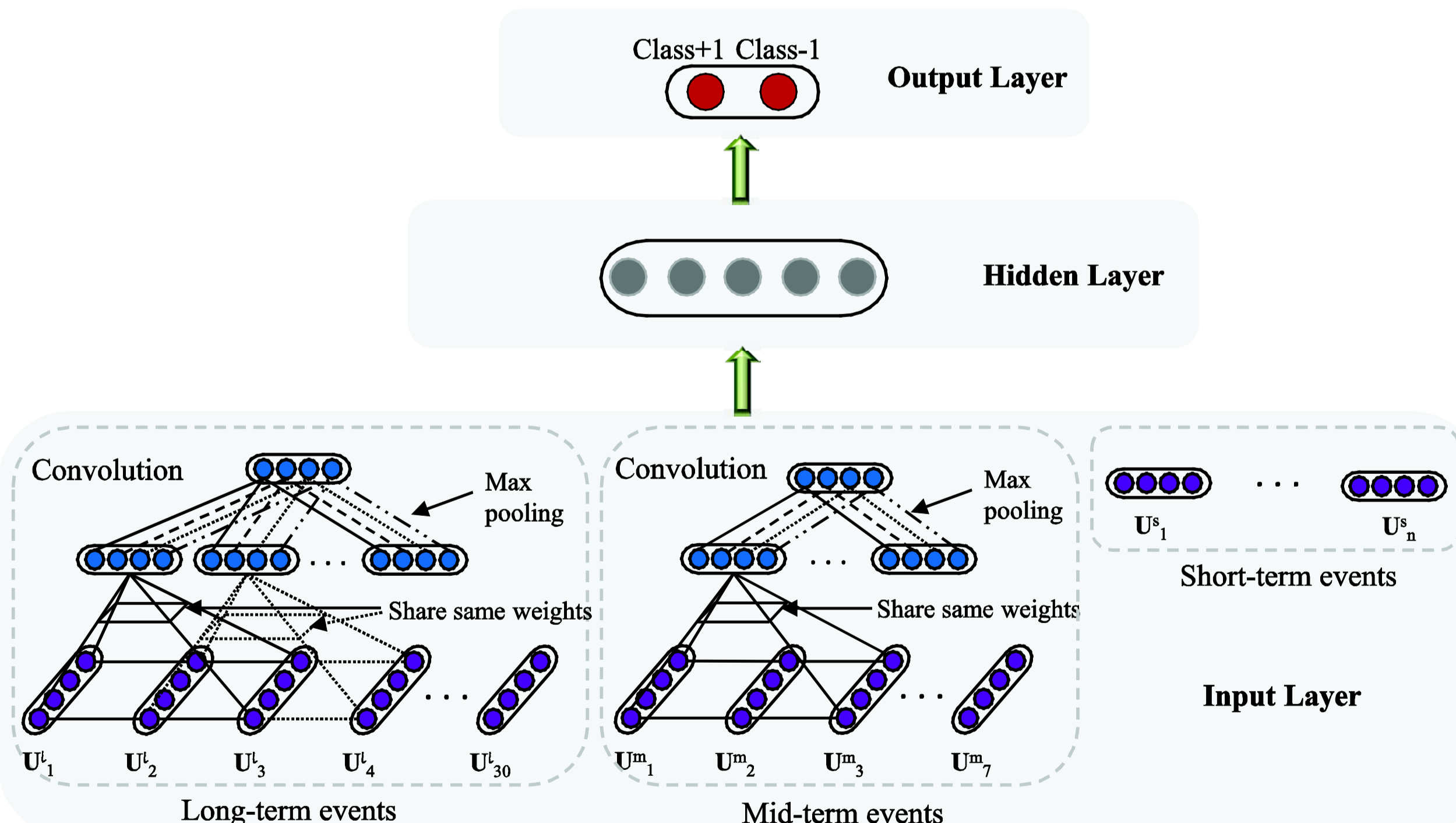
Output: updated model $EELM'$

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1 random replace the event argument and got the corrupted event tuple
2  $\mathcal{E}^r \leftarrow (E_1^r, E_2^r, \dots, E_n^r)$ 
3 while  $\mathcal{E} \neq []$  do
4    $loss \leftarrow \max(0, 1 - f(E_i) + f(E_i^r)) + \lambda \|\Phi\|_2^2$ 
5   if  $loss > 0$  then
6     Update( $\Phi$ )
7   else
8      $\mathcal{E} \leftarrow \mathcal{E} \setminus \{E_i\}$ 
9 return  $EELM$ 
    
```

Deep Prediction Model

Architecture



Experiment Results

Data Description

	Training	Development	Test
#documents	442,933	110,733	110,733
#words	333,287,477	83,247,132	83,321,869
#events	295,791	34,868	35,603
time interval	02/10/2006 - 18/06/2012	19/06/2012 - 21/02/2013	22/02/2013 - 21/11/2013

Table 1: Statistics of datasets.

Data Download

http://ir.hit.edu.cn/~xding/index_english.htm/



Index prediction

	Acc	MCC
Luss and d'Aspremont [2012]	56.42%	0.0711
Ding et al. [2014] (E-NN)	58.94%	0.1649
WB-NN	60.25%	0.1958
WB-CNN	61.73%	0.2147
E-CNN	61.45%	0.2036
EB-NN	62.84%	0.3472
EB-CNN	65.08%	0.4357

Table 2: Development results of index prediction.

Individual stock prediction

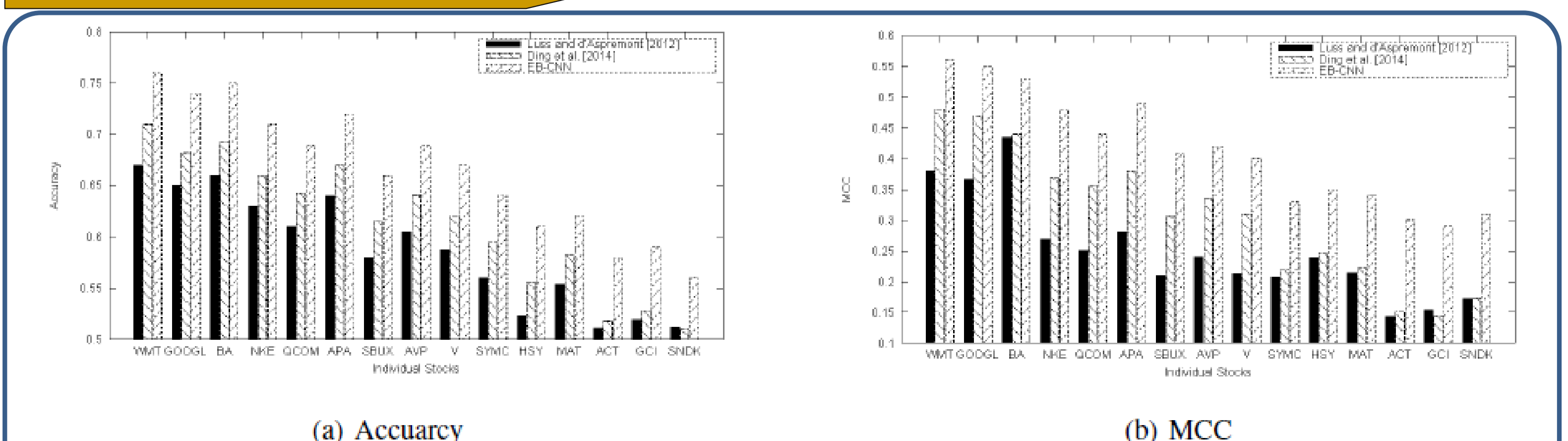


Figure 4: Development results of individual stock prediction (companies are named by their ticker symbols).