

# CRUISE at the NTCIR-10 Mission Impossible Task

Tom A. Cruise  
Disavowed, U.S.A  
toma@cruise.com

Tom B. Cruise  
Disavowed, U.S.A  
tomb@cruise.com

Tom C. Cruise  
Disavowed, U.S.A  
tomc@cruise.com

Tom D. Cruise  
Disavowed, U.S.A  
tomd@cruise.com

Tom E. Cruise  
Disavowed, U.S.A  
tome@cruise.com

Tom F. Cruise  
Disavowed, U.S.A  
The Last Samurai  
Corporation, Japan  
tomf@cruise.com

## ABSTRACT

The CRUISE team participated in the Climb the Dubai Tower (CDT) subtask of the NTCIR-10 Mission Impossible Task. This minority report describes our approach to solving the CDT problem and discusses the official results.

## Team Name

CRUISE

## Subtasks

Climb the Dubai Tower (Chinese, English, Japanese)

## Keywords

eyes wide shut, top gun

## 1. INTRODUCTION

The CRUISE team participated in the Climb the Dubai Tower (CDT) subtask of the NTCIR-10 Mission Impossible Task [1]. This minority report describes our approach to solving the CDT problem and discusses the official results.

## 2. METHOD

### 2.1 RUN1

### 2.2 RUN2

We adopt a method that using a word co-occurrence network. This method has following 3 parts:

1. Make Network
2. Extract Subnetwork
3. Output Rank Result

#### 2.2.1 Make Network

In this part, we make a word co-occurrence network from pairs of post tweets and reply tweet. As well as in the previous section, the data has 0000000 tweets. First, we analyze morphenom against all tweet pairs by MeCab. Then we extract pair of sets of noun words from each pair as  $(W_p, W_r)$ .  $W_p$  or  $W_r$  contains a ordered word set which means faster word appear faster in the original tweet. And set  $V$  as an union of all pairs.

1.  $W_p = (\omega_{p1}, \omega_{p2}, \dots, \omega_{pi} \dots \omega_{pn})$
2.  $W_r = (\omega_{r1}, \omega_{r2}, \dots, \omega_{ri} \dots \omega_{rn})$
3.  $P = W | W \in \bigcup W_p \wedge W \in \bigcup W_r$
4.  $V = \bigcup (W_p, W_r)$

Using  $V$  as nodes, we make a directed graph. We make a path from the first word in some tweet to the next word in the tweet and from each word in  $W_p$  to all words in  $W_r$ .

$$E = \{(\omega_1, \omega_2) | \omega_1 \in W_p \vee \omega_2 \in W_r\} \\ \cup \{(\omega_{pi}, \omega_{p(i+1)}) | 0 < i < n - 1\} \\ \cup \{(\omega_{ri}, \omega_{r(i+1)}) | 0 < i < n - 1\} \quad (1)$$

$$X = v_0 t + \frac{1}{2} a t^2 \\ - (Y_1 + l_2) \\ + abc \quad (2)$$

At last a word co-occurrence network  $G$  is defined like below:

$$G := (V, E)$$

This word network shows what word likely appear next to some word. In other words, it shows that how words close to each other. So, it represents word distribution which contains topic distribution.

#### 2.2.2 Extract Subnetwork

Test tweet data is same as the data used in RUN1. As well as previous part, we extract set of noun words from each test tweet as  $W_t = (\omega_{t1}, \omega_{t2}, \dots, \omega_{ti} \dots \omega_{tn})$ . In this part, we extract subnetwork  $G'_i$  which contains  $\omega_{ti}$  from  $G$ . If  $\omega_{ti}$  exists in  $V$ , pick up all nodes which is next to  $\omega_{ti}$ .

$$V'_i = \omega_{ti} \cup \{\omega_e | (\omega_{ti}, \omega_e) \in E\}$$

$$E'_i = \{(\omega_{ti}, \omega_e) | (\omega_{ti}, \omega_e) \in E\}$$

Finally, we get a subnetwork  $G'$  like below:

$$G'_i = (V'_i, E'_i)$$

$G' = \bigcup G'_i$  represents potential topics of expected replies.

### 2.2.3 Output Rank Result

In this part, we get results for each  $W_t$  using subnetworks we get previous part. We rank each possible reply using tf-idf like score and pagerank.

First, we calculate pagerank for each word in  $W_t$ . With  $E(\omega_k)$ , which is the number of edges that has  $\omega_k$  as the start node, a pagerank is calculated like below:

$$PR(\omega_{ti}) = \frac{(1-d)}{N} + \sum_{\omega_k \in V'_i} d \left( \frac{PR(\omega_k)}{E(\omega_k)} \right)$$

Then, we calculate final score with tf-idf like score.  $P'$  is a set of tweets which concludes  $\omega_{ti}$ .

$$P'_{ij} = \{W_j | W_j \in P \wedge \omega_{ti} \in W_j\}$$

And, we define  $df$  as the number of tweets in  $P'$ ,  $N$  as the number of tweets in  $P$ ,  $l$  as the number of word in  $W_i$ , and  $tc$  as how many  $\omega_{ti}$  appear in  $W_i$ .

1.  $df_i = n(P'_{ij})$
2.  $N = n(P)$
3.  $idf = \log \frac{N}{df} + 1$
4.  $l_i = n(W_j)$
5.  $tc_i = n(\{\omega | \omega = \omega_{ti} \wedge \omega \in W_j\})$

Finally, the score like below:

$$Score_{W_j} = \sum_i \frac{l - tc + 1}{l} idf PR(\omega_{ti})$$

Following this score, our system return the rank list of  $W_j$  against each test data  $W_t$

### 2.2.4 Two types of system

We analyzed result of this run. We considered that continuous “w” was noise. So, we remove morpheme include continuous “w”. Our submission of Run2 is type of not removed “w”, and Run3 is type of removed “w”.

## 3. ADDITIONAL AUTHORS

Additional authors: Tom G. Cruise (Disavowed, U.S.A. email: tomg@cruise.com) and Tom H. Cruise (Disavowed, U.S.A. email: tomh@cruise.com).

## 4. REFERENCES

- [1] T. I. Cruise and T. J. Cruise. Overview of the NTCIR-10 mission impossible task. In Proceedings of NTCIR-10, pages 1–100, 2013.