Information Recall Support for Elderly People in Hyper Aged Societies

Hsin-Hsi Chen¹ and Manabu Okumura²

¹National Taiwan University, Taiwan
²Tokyo Institute of Technology, Japan
Joint Call for Proposal
ICT for Care and Support of Elderly People in
Hyper Aged Societies

• Japan and Taiwan both face the challenges of rapid aging of population.
  • Japan has crossed into a hyper-aged society since 2007.
  • Taiwan is expected to transit to an aged society by 2018 and hyper-aged society by 2025.

• Research areas/topics
  • Utilizing VR and Robot for body augmentation and telework of elderly
  • ICT for the support of independent life of elderly people to achieve their aging in place
  • Monitoring technology for care of elderly people
Basic Information of the International Project

• Period: April 1st 2017~March 31st 2020
• Funders: MOST (Taiwan) and JST (Japan)
• Theme: ICT for the support of independent life of elderly people to achieve their aging in place
• PIs: Professors Hsin-Hsi Chen and Manabu Okumura
• Project volumes: NTD4.74 million and JPY17.55 million (USD311,950 or EUR267,675)
• Project web site-http://nlg.csie.ntu.edu.tw/most-jst-joint-project/
Research Goals

• Investigate together the crucial issues behind the hyper aged societies
• Develop technologies and systems to provide information recall support for elderly people at the right time and at the right place
  • Investigate life-logging mechanisms to keep digital traces generated by individual people
  • Extract entities, properties, relations, and events from her/his life-logging
  • Construct the personalized knowledge base
  • Allow flexible knowledge base access
  • Present recall information to support people daily life
Life Log—Personal Big Data

5月5日 星期六
誰來晚餐，國信家

Sat Apr 01 10:37:04 +0000 2017 tweeted: 去動物店幫小虎補充貓罐頭，結賬時店員問：「你養的是什麼狗？」我笑著小聲答道：「是貓咪，米克司。」結果店員連數秒，我還是忍不住笑出聲來，說：「你太累了。」欸，真是沒禮貌。

Thu Feb 09 09:58:39 +0000 2017 tweeted: 探店中 @ 新埔菜市場

Tue Jan 24 04:41:04 +0000 2017 tweeted: 收到一份小禮物

Sat Dec 24 09:25:03 +0000 2016 tweeted: 在附近上完課後，又來了。可愛的書，安靜的所在，入場費200元，再加50元就可喝到香甜的阿里山泉水紅茶，杯蓋都好看。@ 薄霧書店

誰來晚餐，國信家
Entities, Relationships, Life Events along Timeline

Spouse  
Friend  
Trip  
Party  
Job  
Birthday
Application Scenario of Information Recall

• Memory Loss: Common Seen in Daily Life
Memory vs. Knowledge Base

• Memory
  • Encoding, Storage, and Retrieval
  • Entities joining into an event are encoded as sensations.
  • The sensations and their associations are stored in memory.
  • Some cues will be provided to retrieve the sensations.

• Knowledge Base
  • Extraction, Representation, Retrieval
  • Triple is extracted from natural language statement.
  • Triple is mapped and stored in knowledge base.
  • Knowledge is retrieved by query.
Personalized Knowledge Base

• Knowledge base construction for the memory recall
• Use of the digital traces generated daily
  • Focus on written/spoken data
• Know when people needs the service and provide answers based on their private memory
Personal Knowledge-Based Memory Recall

**Reactive Mode**

Knowledge Representation → Information Extraction → Life Logging → Knowledge Base Retrieval

**Proactive Mode**

Knowledge Representation → Information Extraction → Life Logging → Knowledge Base Retrieval

Turn Detection → Need Detection
Challenging Issues in Proactive Mode

• (1) Detect the turn of the elderly people in the conversation
• (2) Capture the need of information recall service from elderly people
• (3) Tell the types of information recall for the services
• (4) Find the answers for the services if the intention is clear
• (5) Guide the elderly to recall memory if intention is not clear
From Lifelogs to Personal Knowledge Base
<table>
<thead>
<tr>
<th>Tweet Quadruple</th>
<th>Implicit life event quadruples</th>
</tr>
</thead>
<tbody>
<tr>
<td>出去看一頁台北(Go out to watch Yi Ye Taipei) (使用者[user], 看[watch], 一頁台北[Yi Ye Taipei], timestamp)</td>
<td></td>
</tr>
<tr>
<td>坐在麥當勞喝咖啡看閒書，難得上班前的悠閒時光，腦子裡卻不知覺的在想工作上的事情，我都想給自己發加班工資了(I sit at McDonald, drink coffee, read books, and have a leisure time before work. But I am thinking about working, my salary should increase.) (使用者[user], 在[at], 麥當勞[McDonald], timestamp) (使用者[user], 看[read], 閒書[books], timestamp) (使用者[user], 喝[drink], 咖啡[coffee], timestamp)</td>
<td></td>
</tr>
<tr>
<td>這種好天氣@觀音山(It is a nice day@Guanyin Mountain) (使用者[user], 在[at], 觀音山[Guanyin Mountain], timestamp)</td>
<td></td>
</tr>
<tr>
<td>話說用了@ASUS的手機之後真心覺得不錯#zenfone2 (After using the @ASUS cell phone, I think it is really nice # zenfone2) (使用者[user], 用[use], ASUS的手機[the ASUS cell phone], timestamp)</td>
<td></td>
</tr>
<tr>
<td>一樣一杯冰摩卡，昨天 70 今天 125！呜呜希望天天都半價啊！(The same ice mocha, the shop sold 70 yesterday, but it sells 125 today! I hope the ice mocha will be half-price every day!) (使用者[user], 買[buy], 冰摩卡[ice mocha], timestamp)</td>
<td></td>
</tr>
<tr>
<td>新朋友廟口紅茶(My new favorite drinks is Miaokou black tea.) (使用者[user], 喝[drink], 廟口紅茶[Miaokou black tea], timestamp)</td>
<td></td>
</tr>
<tr>
<td>好久沒來的板橋運動場(I have not been to Banqiao Stadium for a long time) (使用者[user], 在[at], 板橋運動場[Banqiao Stadium], timestamp)</td>
<td></td>
</tr>
</tbody>
</table>
Event Detection in Tweet-based Diary

- People are used to log their life on the social media platform.
- Life event can be expressed explicitly or implicitly in a text description.
  - Phone X!: the user bought a new cell phone (a lifelog denotes an implicit event)
- A description does not always contain life events related to a specific individual.
  - Phone X!: the iPhone X was released (not a lifelog for the individual)
- To tell if there exist any life events and further know their categories is indispensable for event retrieval.
- We explore various models to detect and classify life events in tweets.
Tweets as Diary

• We collect 26,818 Chinese tweets from 18 users who have used Twitter for at least 8 years.

• For each tweet, annotators should answer
  • (1) Does the author describe her/his personal life event in this tweet?
  • (2) If the answer is yes, annotators should annotate its type in advance.

• We further define 11 categories of life events from the annotation result.
  • perception, presence, motion, activity, status, health related, commerce, receive and give, social, time related, and other.
Experimental Results

- **LSTM**: The pipelined system adopts LSTM neural networks. The system first identifies the type of a tweet, and then determines the categories of life events based on the result of the first step.

- **Multi-Task LSTM**: The goal of MTL is to improve the performance of the main task by jointly training on the auxiliary task. In this research, the main task is identifying the types of tweets and the auxiliary task is classifying the categories of life events.

<table>
<thead>
<tr>
<th>Model</th>
<th>Feature</th>
<th>Type of Tweet (acc)</th>
<th>Categories of Event (F1)</th>
<th>Non</th>
<th>Explicit</th>
<th>Implicit</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSTM</td>
<td>word</td>
<td>64.80%</td>
<td>28.70%</td>
<td>2674</td>
<td>588</td>
<td>7</td>
</tr>
<tr>
<td>LSTM + attention</td>
<td>word</td>
<td>64.94%</td>
<td>28.72%</td>
<td>2504</td>
<td>772</td>
<td>0</td>
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<tr>
<td>LSTM</td>
<td>word + POS</td>
<td>64.44%</td>
<td>28.47%</td>
<td>2444</td>
<td>805</td>
<td>0</td>
</tr>
<tr>
<td>LSTM + attention</td>
<td>word + POS</td>
<td>65.27%</td>
<td>28.89%</td>
<td>2512</td>
<td>781</td>
<td>0</td>
</tr>
<tr>
<td>MTL- LSTM</td>
<td>word</td>
<td>64.10%</td>
<td>30.98%</td>
<td>2227</td>
<td>993</td>
<td>14</td>
</tr>
<tr>
<td>MTL-LSTM + attention</td>
<td>word</td>
<td>66.34%*</td>
<td>32.34%*</td>
<td>2510</td>
<td>817</td>
<td>20</td>
</tr>
<tr>
<td>MTL-LSTM</td>
<td>word + POS</td>
<td>65.69%</td>
<td>32.98%*</td>
<td>2476</td>
<td>800</td>
<td>38</td>
</tr>
<tr>
<td>MTL-LSTM + attention</td>
<td>word + POS</td>
<td>66.54%*</td>
<td>32.53%*</td>
<td>2487</td>
<td>829</td>
<td>41</td>
</tr>
</tbody>
</table>

(www 2018, poster)
Information Recall Support System

• Knowledge Base Construction
  • Collecting multimedia data of real-world life experience of individuals, such as their documents, their photos, and their videos
  • Organizing the collected data with a focus on identifying and annotating or indexing events

• Knowledge Base Retrieval -- Retrieving the answer from the user’s knowledge base without any input from her by taking into account the information in a sequence of her utterances as a query

• Information Presentation -- Showing the result of the retrieval to the user
Organizing the Collected Data

- The system first segments raw collected data into meaningful units (events) and provides us with the basic atomic unit of retrieval.

- Annotating events with meaningful semantics supports retrieval. For example, sentiment and emotion should be annotated to the events.

- Those tasks can be realized with text segmentation, named entity recognition, and sentiment and emotion analysis.
Action Mining [Noro et al., COLING/ACL2006]

- To extract writer’s “actions” in blogs
- To identify in what period the actions are performed (morning, afternoon, evening, and night)
The train was more crowded than usual on the way of commuting.

We saw a shooting star from the veranda.
Automatic Construction of Large-scale Sentiment and Emotion Lexicon

- [Patra, et al., IJCNLP 2013], [Torii, et al., WASSA 2011],
- [Takamura, et al., NAACL-HLT 2007],
- [Suzuki et al. IEICE 2007],
- [Takamura, et al., EACL 2006],
- [Suzuki, et al., CICLing 2006],
- [Takamura, et al., ACL 2005]
Automatic Construction of Large-scale Sentiment Lexicon

• We proposed to use a semi-supervised method for classification of evaluative expressions that are represented as tuples.
  • The storage capacity of this HDD is high. \(\rightarrow\) positive
  • The noise of this HDD is high. \(\rightarrow\) negative
  • The color of his hair is black. \(\rightarrow\) neutral
Proposed Method

• We focus on the redundancy:
  *Unfortunately, the storage capacity is low (;_;)*.

• Many clues such as adverbs, exclamation marks, emoticons

• A large amount of unlabeled data is easily obtained. Semi-supervised Learning!
Tuples acquired as labeled

• In about 570 thousand tuples, about 414 thousand are classified as either positive or negative.
  
  • <スープ, 深み, ある> → positive
    (The soup has a hearty taste.)
  
  • <パソコン, 反応, 遅い> → negative
    (The PC is languorous.)
  
  • <ラーメン, *, ぬるい> → negative
    (The noodle is lukewarm.)
Emotion Analysis

• Automatic construction of large-scale emotion lexicon
  • Ekman’s six basic emotions: anger, disgust, fear, happiness, sadness, and surprise
  • Represent a word with a distributed representation such as Word2Vec
  • Construct an emotion classifier for words by a supervised learning framework such as SVMs with an existing small lexicon annotated with emotions as training data
Knowledge Base Retrieval

• The system should detect when the user needs any retrieval from her knowledge base.

• The system should extract a query from the user’s utterances.

• It should be a kind of associative retrieval, where the results can be obtained even when query words are not exactly matched.
Detection of Retrieval Timing

- A key technology in our project
- Start constructing a dialog corpus with scenes where a participant needs to recall something happening in the past
Personalized Associative Retrieval

• Knowledge base retrieval will be realized by calculating the similarity scores between query words from the user and the events in the knowledge base.

• The similarity scores themselves should be personalized and able to be obtained from the personalized knowledge base, since association between words tends to be personal and dependent on the individual experience.

• For example, ‘bears’ are usually associated with animals such as rabbits, but they tend to be associated with football teams for those living in Chicago or those who love a football.
Information Presentation

• We currently assume the user usually carry a tablet device or a smart phone.

• Showing the result of the retrieval on a small display necessitates the technology of text summarization that enables extracting only the important fragment of the information.
Text Summarization

- [Hasegawa, et al., ACL 2017], [Kikuchi, et al., EMNLP 2016],
- [Kikuchi, et al., PRICAI 2016], [Kikuchi, et al., ACL 2014],
- [Morita, et al., ACL 2013], [Morita, et al., IPSJ TOD 2012],
- [Makino, et al., CIKM 2012], [Yoshikawa, et al., ACL 2012],
- [Morita, et al., ACL 2011], [Takamura and Okumura, CIKM 2010],
- [Takamura and Okumura, CIKM 2009],
- [Takamura and Okumura, EACL 2009]
Our Framework of Text Summarization

• Generate readable summaries by flexibly applying sentence compression, sentence fusion, and sentence segmentation

• Readable on small hand-held devices such as smart phones
Summary

• In the first year, we focused on development of the related corpus, and the key technologies.

• In the following two years, we will explore how to integrate the technologies in an information recall system.