Event-Related Query Classification with Deep Neural Networks

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Authors: Sahaj Gandhi, Behrooz Mansouri, Ricardo Campos, Adam Jatowt
Introduction
Introduction

- Pattern on time-series of queries using:
  - Document publish time
  - Query issue time

- Pattern on time-series:
  - Non-event
  - One Time Spike
  - Periodic
  - Aperiodic

Different classes of event-related queries. A. Folk Music (Non-Event Query) B. Death of Steve Jobs (One-time-only) C. Golden Globe (Periodic) D. Ronaldo’s injury (Aperiodic).
Research Goals

- Detecting different type of event-related queries
- Reducing the model dependency on language
  - Removing the need to use text and language parsing tools
- Using the following deep neural networks on time-series data to classify each of the event-related queries into their type:
  - Convolutional Neural Networks (CNNs)
  - Recurrent Neural Networks (RNNs) like Long Short Term Memory (LSTM) Network
  - A combination of the above two models
Previous work

Event-related query classification with:

- **Text + Time series data**
  - Seasonal queries [1]
  - Temporal ambiguous queries [2]
- **Time series data**
  - Seasonal queries [3]

Our work differs from the previous ones in using only time-series data and using deep neural network to classify query type.

LSTM Network-based Architecture

- This model in the past has been used to classify temporal information
- They help understand the underlying structure of the frequency data due to its ability to retain important information over time
- This type of models usually suffer from the problem of vanishing gradients
CNN-based Architecture

- This type of an architecture works well to understand the spatial structure of query data.
- Works on data being represented visually instead of just numbers that represent frequencies.
- Works similar to how human identify patterns in frequency data.
LSTM + CNN Architecture

- LSTM networks help analyze the temporal structure of data
- CNN-based networks analyze the spatial structure
- Using both together would help use the pros of both these networks, while avoiding their cons
DATASET

- 600 queries (150 per category).
- Includes queries from English, Spanish, French, Persian, Chinese, and Russian.
- Google trend data (2004 to 2019) which shows the query frequency on scale of [0, 100].
- Used 3 annotators with agreement level of 0.79.
### DATASET

<table>
<thead>
<tr>
<th>Event-related Class</th>
<th>Event-related Queries</th>
</tr>
</thead>
<tbody>
<tr>
<td>One-time-only</td>
<td>北京奥运会 (Chinese- Beijing Olympics), The Hateful Eight movie, Ibrahim tatlises vurdun (Turkish- Ibrahim tatlises shot).</td>
</tr>
<tr>
<td>Periodic</td>
<td>Winter Olympics, نوروز (Persian- Nowruz), День отца (Russian, Father’s day).</td>
</tr>
<tr>
<td>Aperiodic</td>
<td>Éclipse de lune (French-Lunar eclipse), 津波 (Japanese-Tsunami), Lampard injury.</td>
</tr>
<tr>
<td>Non-event</td>
<td>Puppe für Kinder (German- Doll for children), Church songs, Dynamic programming.</td>
</tr>
</tbody>
</table>
## Experimental Result

<table>
<thead>
<tr>
<th>Model</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>0.72 ▼</td>
<td>0.69 ▼</td>
<td>0.70 ▼</td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>0.65 ▼</td>
<td>0.58 ▼</td>
<td>0.61 ▼</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.62 ▼</td>
<td>0.66 ▼</td>
<td>0.64 ▼</td>
</tr>
<tr>
<td>LSTM</td>
<td>0.82 ▼</td>
<td>0.82 ▼</td>
<td>0.82 ▼</td>
</tr>
<tr>
<td>CNN</td>
<td>0.85 ▼</td>
<td>0.80 ▼</td>
<td>0.82 ▼</td>
</tr>
<tr>
<td>LSTM+CNN</td>
<td><strong>0.88</strong></td>
<td><strong>0.86</strong></td>
<td><strong>0.87</strong></td>
</tr>
</tbody>
</table>

Event-related Query Classification results with neural network and non-neural network models on test data. Boldface indicates the best results.
## Experimental Result

<table>
<thead>
<tr>
<th>Ground Truth</th>
<th>Non-Event</th>
<th>OneTimeOnly</th>
<th>Periodic</th>
<th>Aperiodic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-Event</td>
<td>13</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>OneTimeOnly</td>
<td>0</td>
<td>13</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Periodic</td>
<td>0</td>
<td>0</td>
<td>12</td>
<td>3</td>
</tr>
<tr>
<td>Aperiodic</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>14</td>
</tr>
</tbody>
</table>

Confusion Matrix for LSTM+CNN Model.
Result Analysis - Misclassification

A) Newton’s Second Law (Non-Event classified as Periodic)
B) BlackLivesMatter (One-time only classified as Aperiodic)
C) День отца (Father’s Day in Russian) (A seemingly periodic event being classified as aperiodic)
D) Ronaldo Injury (Aperiodic, but classified as one-time only event)
Result Analysis

Time-series related to query "Audio Book".

Time-series related to query "Encyclopedia" (a) and "Asian Game" (b).
● Presented a new model for classifying event-related queries by considering four classes: “periodic”, “aperiodic”, “one-time-only”, and “non-event”.

● Our model uses only the time-series data built upon query frequency, which allows it to work for any language.

● We used 600 different queries (150 per category) and studied the effectiveness of our model.
- We plan to study how we could extend the current model also to classify different categories of periodic and aperiodic queries.

- Make use of content features. Based on that, we plan to study how using the embedding models such as word2vec or Bert.

- The prediction of the event type instead of doing the detection.
Thanks for your attention.

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For further questions please contact the authors.