INTRODUCTION

Task: Automatically extract useful insights, i.e. the data mining results, from a multi-dimensional table, model their usefulness or interestingness, and rank the top ones.

Challenge: lack of available paired data; multi-dimensional comparison criteria.

Solution:
- Text Assistance
- Ranking Model
- Global Context-Aware Memory

CONTRIBUTIONS

- We formally formulate the problem of text assisted insight ranking, which has not been fully investigated yet.
- We construct a new financial dataset, in which insight importance is labeled with text assistance.
- We propose a context-aware memory network to model the importance of insights. The experimental results on two datasets show that our approach significantly outperforms the baseline methods.

MODEL

Neural Ranking module

The neural ranking model explores the data characteristics, including its semantic information, insight type, statistic information and subspace, and assigns importance scores to each insight.

The model is implemented as a multi-layer perceptron (MLP) and trained by minimizing the L2 loss J(y) of the output scores and the similarity scores of the insights.

Key-Value Memory Network

Additionally, the key-value memory network model introduces other insights within one group, namely the table context, into the ranking process.

EXPERIMENT

We conduct experiments on Financial Report Dataset and SBNation Dataset (Wiseman et al., 2017).

Financial Report Dataset Statistics

The dataset contains in total 5,670 reports and 49,129 tables of 2,762 companies from United States Securities and Exchange Commission.

Accuracy of Text Assistance Method

We randomly sample 4,000 pairs of insights and their most similar sentences in the reports, and ask 10 annotators to label whether the pairs are of the same meaning.

Evaluation Results on SBNation Dataset

<table>
<thead>
<tr>
<th>Models</th>
<th>Precision@1</th>
<th>Precision@3</th>
<th>Precision@5</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBScluster</td>
<td>0.727</td>
<td>0.629</td>
<td>0.540</td>
</tr>
<tr>
<td>TARmemory</td>
<td>0.866</td>
<td>0.813</td>
<td>0.745</td>
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</table>

Evaluation Results on Financial Report Dataset

<table>
<thead>
<tr>
<th>Models</th>
<th>Precision@1</th>
<th>Precision@3</th>
<th>Precision@5</th>
<th>mAP@3</th>
<th>mAP@5</th>
<th>NDCG@3</th>
<th>NDCG@5</th>
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<tbody>
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<tr>
<td>TARrun</td>
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<td>0.425</td>
<td>0.626</td>
<td>0.684</td>
<td>0.772</td>
<td>0.812</td>
<td>0.829</td>
</tr>
</tbody>
</table>

Case Study

It consists of the top 5 insights in 10 insight candidates from one table. The reason why the fourth insight is wrongly labeled is that the similarity score is incorrectly calculated and the gold standard is in fact inaccurate. This serves as an example of the optimization direction.

MISC

References


Links:

arxiv.org/abs/1811.05563

Scan QR code to view the paper