Predicting Clinical Events Based On Raw Text: From Bag of Words to Attention-Based Transformers

Dmitri Roussinov, Andrew Patterson
University of Strathclyde

Andrew Conkie       Christopher Sainsbury
Red Star Consulting  NHS Greater Glasgow & Clyde

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Pt placed on a spont breathing trial @ 13:00, pt resp one time within 10 sec - unfortunatly his SBP droppd from 100 to 70 rapidly and therefore the trail was d/c`ed.
Cardiac: BP stable 120-130/60. Pt is on Amiodarone via NGT TID. Tolerating this well. HR 80–95 most of the shift. Has rare to occ. Swan numbers done Q6hrs as ordered and probably swan will come out today He remains on heparin drip which needed to be decreased to 750u/hr at 11PM for PTT 110

• Domain-specific terminology and abbreviations
• Typos
• Grammatical/lexical variation typical for natural language: can convey similar information in many different ways
The Task

– Predicting Clinical Events Based On Raw Text
  • E.g. patient readmission within 30 days of discharge, patient death within a year, etc.

– Solution Primarily Focused: pre-trained language models such as Bert, Elmo, GPT or T5

– As baseline: classical bags of words classifiers, recurrent/convolutional neural networks, pre-trained word embeddings

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Prior Works

• Some successful applications ($ROC > .70$ practicality threshold)
• Rarely only raw text, often with categorical and numerical attributes
• Not clear if any deep neural approaches work better than classical “bag of words” models
Pre-trained Language Models (BERT)

- Impacted **most** applications of *NLP* and *text analytics* in various domains
- Capture the *distribution of word sequences* in a language (or in a specific domain like medical)
- The most popular ones are *attention-based transformers* (e.g. BERT)
- Fundamental limitation: number of input *tokens* (roughly 512)
  - which roughly translates to 250 words.
  - 8 times less than we need on average
Combining The Text Segments

- Transformer models use “classification token” \((CLS = \text{the vector representing the very first input token on the highest layer})\)
- We split the long texts into \textit{segments} and combine \textit{CLS}s or all top vectors from those segments. Specifically, we’ve tried:
  - LSTM of CLSs
  - LSTM of all top vectors
  - Concatenation of CLSs
  - Average/min/max of CLSs

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Dataset: MIMIC-III

- Very popular dataset
- Sixty-thousand Intensive Care Unit (ICU) admissions
- We used discharge summaries from adult patients
- Roughly 30 thousands records
- No special pre-processing for numbers or abbreviations

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Results: compared with baselines

<table>
<thead>
<tr>
<th>Model</th>
<th>Re-admission AUC</th>
<th>Death within a year AUC</th>
<th>Death or re-admission AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bag-of-words</td>
<td>0.713</td>
<td>0.844</td>
<td>0.763</td>
</tr>
<tr>
<td>Deep Neural models:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean-Pooling Word Embeddings</td>
<td>0.743</td>
<td>0.871</td>
<td>0.788</td>
</tr>
<tr>
<td>CNN</td>
<td>0.739</td>
<td>0.867</td>
<td>0.787</td>
</tr>
<tr>
<td>RNN</td>
<td>0.738</td>
<td>0.873</td>
<td>0.785</td>
</tr>
<tr>
<td>Transformer general</td>
<td>0.715</td>
<td>0.776</td>
<td>0.778</td>
</tr>
<tr>
<td>Transformer medical</td>
<td>0.741</td>
<td>0.871</td>
<td>0.786</td>
</tr>
</tbody>
</table>

- “AUC” = area under the ROC curve
- Mean-Pooling Word Embeddings AKA “Fast Text”, is essentially a deep neural “bag or word” model (ignores the word order, but models word interaction)
- “Transformer general” = BERT
- “Transformer medical” = Clinical BERT by Alsentzer et al.
## Results: transformer input size limitation

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<th>Death within a year</th>
<th>Death or re-admission</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSTM CLS</td>
<td>0.741</td>
<td>0.871</td>
<td>0.786</td>
</tr>
<tr>
<td>LSTM on top layer</td>
<td>-10%</td>
<td>-8%</td>
<td>-9%</td>
</tr>
<tr>
<td>Concat top layer</td>
<td>-12%</td>
<td>-11%</td>
<td>-13%</td>
</tr>
<tr>
<td>Concat CLS</td>
<td>-2%</td>
<td>-4%</td>
<td>-2%</td>
</tr>
<tr>
<td>Average pool CLS</td>
<td>-15%</td>
<td>-10%</td>
<td>-15%</td>
</tr>
<tr>
<td>Min pool CLS</td>
<td>-22%</td>
<td>-16%</td>
<td>-21%</td>
</tr>
<tr>
<td>Max pool CLS</td>
<td>-17%</td>
<td>-13%</td>
<td>-16%</td>
</tr>
</tbody>
</table>
Conclusions

• All our models reach AUC > .70, which is practically useful level of performance
• Pre-trained transformer-based LM worked only as good as much simpler Fast-Text
• And even only after
  – It was pre-trained on medical texts
  – the input size limitation has been addressed

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Ideas For Future

• More datasets
• More experiments with combining several segments
• More advanced pre-trained models (T5, GPT2, Longformer, Reformer, Performer, and BigBird)
  – Can handle longer texts
  – No medical versions exist yet
Questions?

• Are welcome by email

  dmitri dot roussinov at strath.ac.uk

  Or co-authors.