Assessment of Content and Structure of Clinical Notes at an Academic Medical Center

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Background

- Data from the EHR provides the opportunity to use real-world and real-time information to assess outcomes and improve predictive models
- It is estimated that 80% of healthcare data are unstructured sources, such as clinical notes
- Extracting relevant features from unstructured sources is a complex process, and descriptive statistics about the content are not well-described
- The ability to copy-forward notes within the EHR potentially introduces outdated, inaccurate, or unnecessary information

Objectives

- Describe the content and diversity of clinical notes within a large, academic healthcare system
- Identify potential features that can be used for feature engineering in downstream models, such as note similarity, frequency, and distribution

Methods

- All clinical notes from Yale New Haven Hospital from January 2014 through December 2015
- Notes extracted in delimited file and converted to JSON, then analyzed with custom Python scripts

Clinical Notes → JSON → Python

- Assessed basic descriptive statistics and lexical content stratified by note type, encounter type, and author specialty
- Type–Token Ratio (TTR) = \( \frac{\text{Number of unique tokens (Vocabularies)}}{\text{Number of tokens (words)}} \)
- Calculated the similarity for each combination of H&P, ED notes, and progress notes for two patients to assess the feasibility of similarity analysis in free-text notes

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Results

- Nearly 1 million unique patients
- 25 million clinical notes
- 20 note features extracted, including note text

Features for YNHH Clinical notes

- 28.2 notes (SD=64.5)
- 5.4 note types (SD=5.9)
- 3.1 encounters (SD=2.3)
- 3.7 specialties (SD=2.4)

Note Features

- Progress Notes
- Encounters (Hospital, outpatient, etc.)
- Author specialties (IM, EM, etc.)

Data and Lexical Diversity by Top 10 Note Types

<table>
<thead>
<tr>
<th>Note Type</th>
<th>% Types</th>
<th>Average # Tokens</th>
<th>Average Words</th>
<th>Average Sentences</th>
<th>Average # Words/Sentence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Progress Notes</td>
<td>30.3%</td>
<td>348.8</td>
<td>479</td>
<td>25.5</td>
<td>22.6</td>
</tr>
<tr>
<td>Emergency Evaluation</td>
<td>25.0%</td>
<td>234.8</td>
<td>316.4</td>
<td>19.5</td>
<td>27.9</td>
</tr>
<tr>
<td>Plan of Care</td>
<td>17.2%</td>
<td>103.1</td>
<td>516.4</td>
<td>12.2</td>
<td>25.6</td>
</tr>
<tr>
<td>ED Notes</td>
<td>5.2%</td>
<td>52.9</td>
<td>52.8</td>
<td>6.2</td>
<td>12.2</td>
</tr>
<tr>
<td>Patient Instructions</td>
<td>6.8%</td>
<td>158.5</td>
<td>502.1</td>
<td>35.2</td>
<td>14.1</td>
</tr>
<tr>
<td>ED Provider Notes</td>
<td>3.8%</td>
<td>378.8</td>
<td>717</td>
<td>40.7</td>
<td>16.2</td>
</tr>
<tr>
<td>H&amp;P</td>
<td>2.8%</td>
<td>52.8</td>
<td>754.8</td>
<td>31.5</td>
<td>18.4</td>
</tr>
<tr>
<td>Consult Note</td>
<td>1.3%</td>
<td>423.9</td>
<td>942.5</td>
<td>40.1</td>
<td>26.7</td>
</tr>
<tr>
<td>ED/OP Note</td>
<td>1.2%</td>
<td>223.7</td>
<td>500.6</td>
<td>35.2</td>
<td>20.1</td>
</tr>
<tr>
<td>All Notes</td>
<td>100%</td>
<td>158.6</td>
<td>325.4</td>
<td>23.9</td>
<td>16.7</td>
</tr>
</tbody>
</table>

Conclusions

- These data provide a comprehensive, descriptive assessment of the diversity in unstructured notes
- Multiple features can be rapidly extracted which may be beneficial in downstream analytic models
- Future work will apply these foundational data and results to predictive models, such as operative risk scores, to assess whether unstructured content can improve predictive accuracy