1. Introduction

- YouTube has gained popularity among multi-billion dollar company marketers.
- YouTubers exploit this opportunity to make money: advertisements ⇒ Offer money for each view where the video being compliant with stipulated advertisement-friendly guidelines.
- Leads to clickbait ⇒ provokes users to click on videos using attractive titles and thumbnails.
- Users end up watching a video that does not have the content as publicized in the title.
- Why? Humans have the need to explore and fill the knowledge gap between what they know and what they wish to know [Information gap theory].
- Clickbait exploits this gap by using the Title and Thumbnail.

2. Research Gap

- Clickbait detection for web pages and articles - available and well researched.
- Video clickbait detection - only a handful of research is available.
- No implementation of a model with an architecture with audio transcript and other important cues such as titles, tags etc. are taken into account.

3. Research Purpose

✓ Address the Clickbait video issue on YouTube ⇒ develop an algorithm (BaitRadar) using a multi-model deep learning architecture.
- Effectively and efficiently detect Clickbait on YouTube.

4. Significance of Study

The BaitRadar algorithm:
• Combines multiple cues in a YouTube video to make inferences.
• Exploits the audio transcript of the video in tandem with other cues in the video.
• Achieves more resilience against missing data ⇒ a more robust classification approach against the conventional methods.

5. Data and Methodology

- Dataset gathering and pre-processing.
- Training and evaluation of individual models.
- Multi-model architecture

6. Experiments and Findings

- Model implementation: Tensorflow with Keras using Python and trained on Nvidia RTX 2080 Ti.

Table 1: Detection accuracy from individual models

<table>
<thead>
<tr>
<th>Model</th>
<th>Training Accuracy</th>
<th>Validation Accuracy</th>
<th>Testing Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Audio Transcript</td>
<td>99.09</td>
<td>94.12</td>
<td>93.80</td>
</tr>
<tr>
<td>Title</td>
<td>94.29</td>
<td>87.20</td>
<td>87.30</td>
</tr>
<tr>
<td>Thumbnail</td>
<td>90.61</td>
<td>90.61</td>
<td>81.43</td>
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<tr>
<td>Comments</td>
<td>98.64</td>
<td>96.40</td>
<td>98.80</td>
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<tr>
<td>Tags</td>
<td>99.83</td>
<td>98.76</td>
<td>98.70</td>
</tr>
<tr>
<td>Statistics</td>
<td>78.69</td>
<td>78.69</td>
<td>77.78</td>
</tr>
</tbody>
</table>

- Highest individual accuracy: Tags model ⇒ Reason? As clickbait videos contain higher number of tags for tricking the YouTube recommendation algorithm.

Fig. 2: Summarised results for different combinations

- Combination of 6 models: Highest accuracy (~98%) with an inference time of ≤ 2s ⇒ Reason? It has the most data to train and infer with = BaitRadar.
- Combining all models ⇒ takes more epochs on average to converge against other models. Reason? Because each (sub-)model is contributing to the overall accuracy.

7. Limitation and Conclusion

- Issues with borderline cases ⇒ videos that are not clearly clickbait: from the perspective of a subscriber and non-subscriber.
- Given the results and analysis ⇒ BaitRadar performs as intended.
- Future work: explore the performance of the model on various kinds of media ⇒ aiming to understand different insights through model interpretability to better detect clickbait videos.