

Discovery and Scaling of Text Models for Authorship Attribution

Porter Bagley
Computing - DSSI

Collaborators: Juanita Ordonez, Rafael Rivera Soto



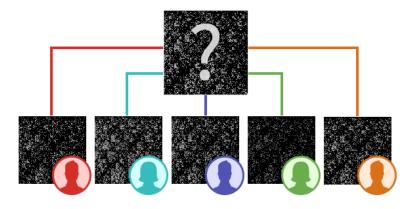


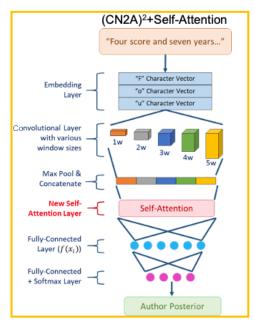
Introduction



Motivation:

- As more of us rely on online sources for news and information, it becomes increasingly important to verify their authenticity
- Authorship attribution can help us determine trustworthiness





Our team created a CNN architecture which used Attention and performed well

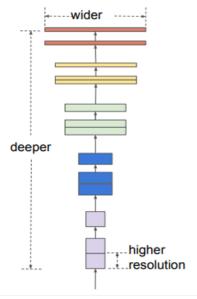
• Questions:

- How to scale a CNN model strategically?
- Is this the best architecture?

Methods



- Compound Scaling
 - "EfficientNet: Rethinking Model Scaling for CNNs" (Tan & Le, 2019)
 - Rather than searching for the best dimensions with a huge model, find the best dimensions on a small model, then scale up proportionally



 We apply the methods from EfficientNet to text-based data

depth:
$$d=\alpha^{\phi}$$
 width: $w=\beta^{\phi}$ resolution: $r=\gamma^{\phi}$ s.t. $\alpha\cdot\beta^2\cdot\gamma\ \approx 2$ $\alpha\geq 1, \beta\geq 1, \gamma\geq 1$

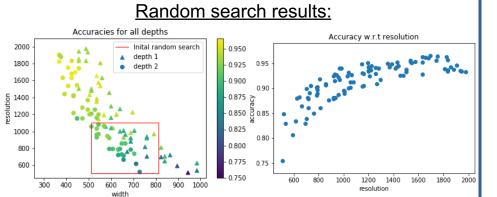
- Dataset
 - 100 authors from Reddit
 - Documents of 100-500 characters
 - Concatenated according to timestamp and subreddit to make 2000 & 5000 character length datasets



Results and Conclusion



Results



Top model results:

Scaling	Average	Performance of Scaled Model
amount	Author Accuracy	0.98 -
1.0 (original)	0.8286	0.96 - 0.94 - 5 0.92 - 0.90 - 0.88 - 0.86 - 0.84 -
2.0	0.9254	
4.0	0.9399	
8.0	0.9601	
16.0	0.9728	
20.0	0.9900	0 2 4 6 8 10 12 14 16 18 20 scaling multiplier (x times # of FLOPS)

Conclusion

- Compound scaling is effective for textbased CNNs
- Increasing the resolution of text-based data can lead to large gains in performance
- Achieved 99.0% (+16.1%) accuracy on authorship attribution task

Next Steps

- Discover alternate architectures using TextNAS (Wang et al., 2019)
- Apply similar methods to open-world authorship attribution task





Disclaimer

This document was prepared as an account of work sponsored by an agency of the United States government. Neither the United States government nor Lawrence Livermore National Security, LLC, nor any of their employees makes any warranty, expressed or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States government or Lawrence Livermore National Security, LLC. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States government or Lawrence Livermore National Security, LLC, and shall not be used for advertising or product endorsement purposes.

