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Paper Title : Resume Shortlisting and Ranking with Transformers

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Plan of Presentation

Introduction

Related work

Methodology

Results & Discussion

Future scope

Conclusion

References

Introduction

- In a business or organization, it is indeed critical to make the proper hiring decisions for particular positions for Human Resources Manager or Head-hunter.
- All resumes should be manually reviewed to identify possible applicants.
- Especially, large companies like "Google" frequently receive thousands of resumes each year for job applications.
- This paper aims to reduce the screening time of resumes and shortlist the best N number of engineers for the interview process based on the job description.
- As a result, automation is introduced to make the work easy with time-saving.

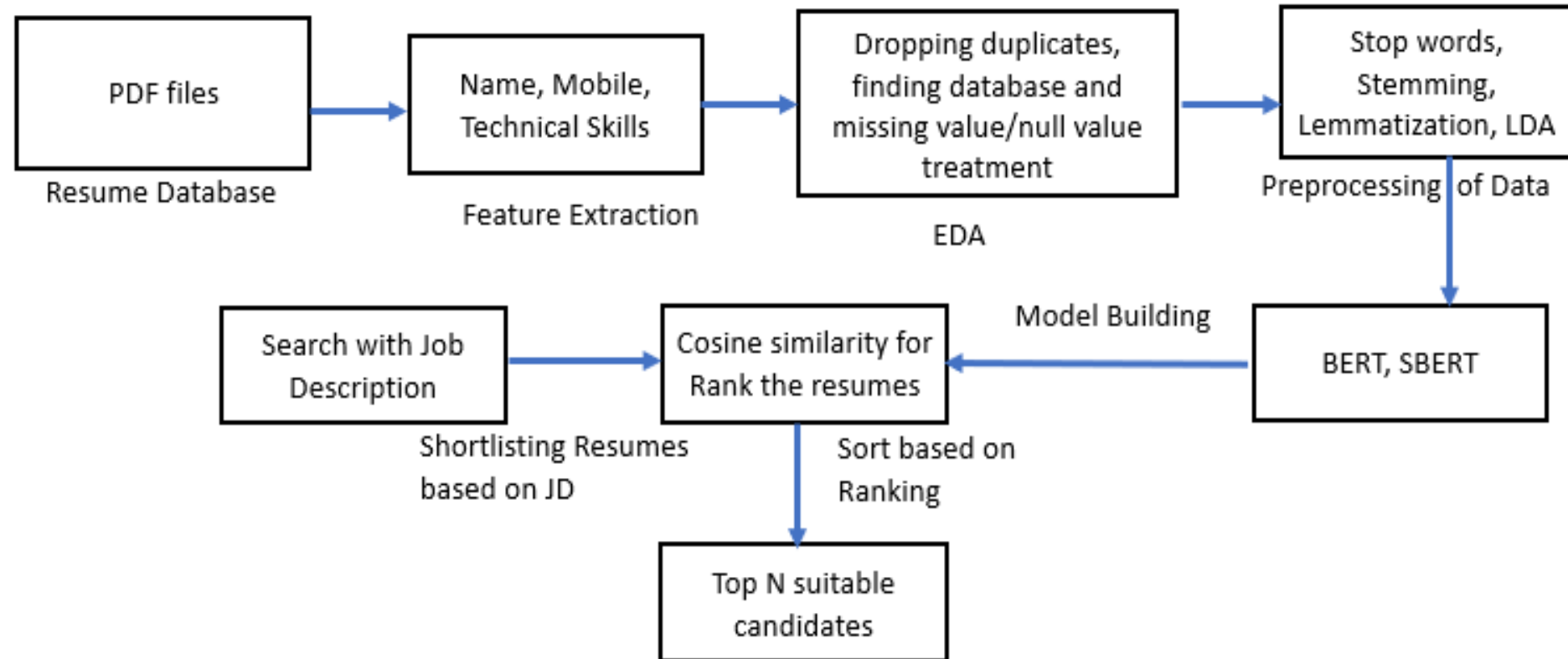
Related work

Title of papers	Author and Year	Major Insights	Reserch Gap
Attention is all you need. Advances in neural information processing systems.	Vaswani et al. 2017 [1].	<ol style="list-style-type: none"> 1. Transformer, a model architecture entirely on an attention mechanism to draw global dependencies between input and output and overcomes the parallelization problem. 2. A self-attention network for the neural sequence-to-sequence task. 3. Transformer allows for significantly more parallelization and can reach a new state of the art in translation quality. English-to-German translation task: BLEU score of 28.4 English-to-French translation task: BLEU score of 41.0 	<ol style="list-style-type: none"> 1. Extend the Transformers to address problem to efficiently handle large inputs and outputs such as images, audio, and videos.
BERT: Pre-training of deep bidirectional transformers for language understanding.	Devlin et al. 2019 [2].	<ol style="list-style-type: none"> 1. Introduced a new language representation model called BERT. 2. Improved the fine-tuning-based approaches by proposing BERT: Bidirectional Encoder Representations from Transformers. 3. BERT, a deep bidirectional Transformers model: Mask Language Model (MLM) and Next Sentence Prediction (NSP). 4. The experiments demonstrate that BERT is effective for both fine-tuning and feature-based approaches. 5. It obtains new state-of-the-art results on eleven natural language processing tasks, including pushing the GLUE score to 80.5%. 	<ol style="list-style-type: none"> 1. For auto-regressive tasks there is no clear way of training BERT. 2. Since it is bidirectional and inputting the target during training would lead to a target leakage.

Related work

Title of papers	Author and Year	Major Insights	Reserch Gap
Sentence-bert: Sentence embeddings using siamese bert-networks	Reimers et al. 2019 [3].	<ol style="list-style-type: none"> 1. Introduce Sentence-BERT (SBERT), a modification of the pretrained BERT network that use siamese and triplet network structures to derive semantically meaningful sentence embeddings that can be compared using cosine-similarity. 2. This reduces the effort for finding the most similar pair from 65 hours with BERT / RoBERTa to about 5 seconds with SBERT, while maintaining the accuracy from BERT. 	<ol style="list-style-type: none"> 1. SBERT is computationally efficient enabling it to be used in real-time applications such as semantic search. 2. For activities that BERT cannot model due to computing constraints, SBERT can be used.
Evaluation of BERT and ALBERT Sentence Embedding Performance on Downstream NLP Tasks.	Choi et al. 2021 [4].	<ol style="list-style-type: none"> 1. This paper explores on sentence embedding models for SBERT and SALBERT. 2. Experimented with an outer CNN sentence-embedding network for SBERT and SALBERT. 3. CNN architecture improves ALBERT models substantially more than BERT models for STS benchmark. 4. The performance of SALBERT catches up with SBERT when the CNN architecture applies, but CNN-SALBERT is still slightly inferior to CNN-SBERT. 	<ol style="list-style-type: none"> 1. Evaluation of sentence embedding with larger ALBERT models—i.e., ALBERT-large and ALBERT-xlarge.
Improving the Performance of the Extractive Text Summarization by a Novel Topic Modeling and Sentence Embedding Technique using SBERT.	Mandala et al. 2021 [5].	<ol style="list-style-type: none"> 1. A cluster-based automatic text summarization system using SBERT to perform sentence embedding and topic modeling processes to improve the summarization technique. 2. Result shows that the application of SBERT for sentence embedding, topic modeling and calculation of cosine similarity can improve the quality of the resulting summary because SBERT can represent the semantic meaning of sentences better. 	<ol style="list-style-type: none"> 1. Many variants of the pre-trained SBERT model can be compared or need to try with different scoring methods like Named entity recognition. 2. It is also necessary to refine the parameter tuning procedure to find a more precise combination of parameters.

Methodology

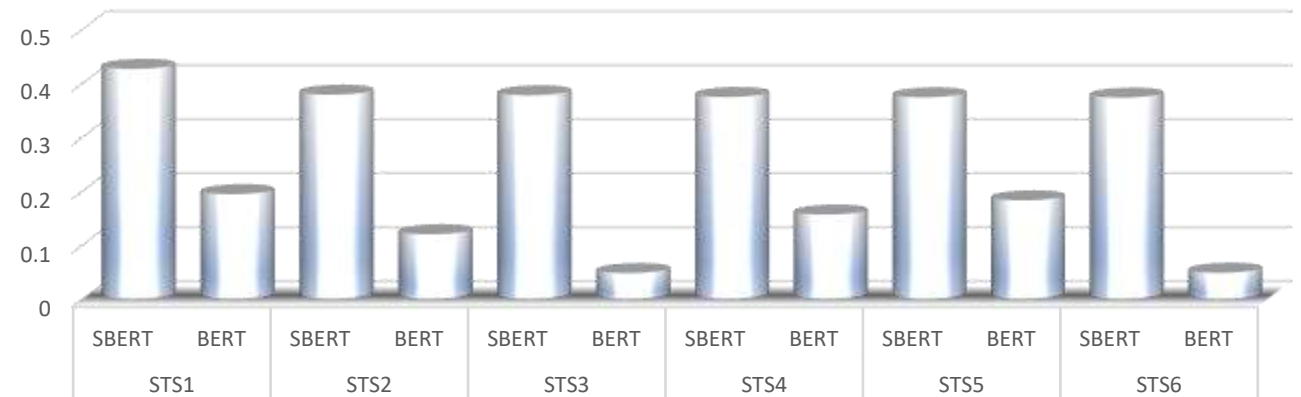


Results & Discussion

- Sentence embedding that outperforms the Classical Least Squares (CLS) vector is obtained by the average of the SBERT context embedding's one or two layers.
- The degree of semantic similarity among top-ranking terms in each topic is measured by correlativity.
- SBERT gives better solution than BERT when a comparison of top ten ranked resumes based on JD.

Data Set	Model	Correlation value for Similarity
STS1	SBERT	0.42649
	BERT	0.194206
STS2	SBERT	0.378602
	BERT	0.119996
STS3	SBERT	0.377433
	BERT	0.047986
STS4	SBERT	0.374302
	BERT	0.156387
STS5	SBERT	0.373682
	BERT	0.182748
STS6	SBERT	0.373111
	BERT	0.048559

Correlation value for Similarity



Future scope

- One of the main issues is when a candidate lists skills for which they have no experience because the model focuses on the skill set listed on the resume submitted by the candidate.
- The usage of Artificial Intelligence techniques or any other effective sentence embedding transformers will be made for further improvement.

Conclusion

- The proposed SBERT transformer helps recruiters screen resumes more quickly and effectively, cutting the cost of hiring. Thus, the company will then have access to a potential applicant who will be successfully placed in a business that appreciates the candidate's skills and competencies.
- The SBERT streamlines the process by summarizing resumes and classifying them by how closely they match the organization's necessary skills and requirements.
- The proposed method evaluates candidates' skills and ranks them by the JD and skill requirements of the employing organization.

References

1. Vaswani, Ashish, et al. "Attention is all you need." Advances in neural information processing systems 30 (2017).
2. Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
3. Reimers, N., & Gurevych, I. (2019). Sentence-bert: Sentence embeddings using siamese bert-networks. arXiv preprint arXiv:1908.10084.
4. H. Choi, J. Kim, S. Joe and Y. Gwon, "Evaluation of BERT and ALBERT Sentence Embedding Performance on Downstream NLP Tasks," 2020 25th International Conference on Pattern Recognition (ICPR), 2021, pp. 5482-5487, doi: 10.1109/ICPR48806.2021.9412102.
5. P. S. Suryadjaja and R. Mandala, "Improving the Performance of the Extractive Text Summarization by a Novel Topic Modeling and Sentence Embedding Technique using SBERT," 2021 8th International Conference on Advanced Informatics: Concepts, Theory and Applications (ICAICTA), 2021, pp. 1-6, doi: 10.1109/ICAICTA53211.2021.9640295.

Thank you