



REVA
UNIVERSITY

Bengaluru, India

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REVA Academy for Corporate Excellence (RACE)

Resume Shortlisting and Ranking with Transformers

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In a business or organization, it is indeed critical to make the proper hiring decisions for particular positions for Human Resources Manager or a Head-hunter.

All resumes should be manually reviewed to identify possible applicants. Besides, screening process will take a lot of time and effort.

Especially, large companies like "Google" frequently receive hundreds of thousands of resumes each year for job applications

Our aim of this project is to reduce the screening time of resumes and short list 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.

Literature Review

Seminal works | Summary | Research Gap

Title of papers	Auther and Year	Journal Source	Major Insights	Reserch Gap
Attention is all you need. Advances in neural information processing systems	Vaswani et al. 2017	https://arxiv.org/abs/1706.03762	<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 	Extend the Transformers to address problem to efficiently handle large inputs and outputs such as images, audio and videos.

Literature Review

Seminal works | Summary | Research Gap

Title of papers	Author and Year	Journal Source	Major Insights	Research Gap
BERT: Pre-training of deep bidirectional transformers for language understanding	Devlin et al. 2019	In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1	<ol style="list-style-type: none">1. Introduced a new language representation model called BERT2. Improved the fine-tuning based approaches by proposing BERT: Bidirectional Encoder Representations from Transformers autoencoding pre-trained language model3. BERT, a deep bidirectional Transformers model: Mask Language Model (MLM) and next sentence prediction4. 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.

Literature Review

Seminal works | Summary | Research Gap

Title of papers	Author and Year	Journal Source	Major Insights	Reserch Gap
Evaluation of BERT and ALBERT Sentence Embedding Performance on Downstream NLP Tasks	Choi et al. 2021	2020 25th International Conference on Pattern Recognition (ICPR)	<ol style="list-style-type: none"> 1. This paper explores on sentence embedding models for BERT and ALBERT. 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. ALBERT has a better performance than BERT when fine-tuned on STSb. SALBERT has much lower performance than SBERT. 5. The performance of SALBERT catches up with SBERT when the CNN architecture applies, but CNN-SALBERT is still slightly inferior to CNN-SBERT 	Evaluation of sentence embedding with larger ALBERT models—i.e., ALBERT-large and ALBERT-xlarge

Literature Review

Seminal works | Summary | Research Gap

Title of papers	Author and Year	Journal Source	Major Insights	Reserch Gap
Transformer based contextualization of pre-trained word embeddings for irony detection in Twitter	González et al 2020	Information Processing & Management 57.4 (2020): 102262.	<ol style="list-style-type: none">1. A model for irony detection (English and Spanish) based on the contextualization of pre-trained Twitter word embeddings by means of the Transformer architecture.2. This system was the first ranked system in the Spanish corpus and it has achieved the second-best result on the English corpus	How Multi-head self-attention mechanisms of the Transformer architecture address the irony detection problem.

Literature Review

Seminal works | Summary | Research Gap

Title of papers	Author and Year	Journal Source	Major Insights	Reserch Gap
Improving the Performance of the Extractive Text Summarization by a Novel Topic Modeling and Sentence Embedding Technique using SBERT	Mandala et al. 2021	8th International Conference on Advanced Informatics: Concepts, Theory and Applications (ICAICTA)	<ol style="list-style-type: none">1. A cluster-based automatic text summarization system using Sentence-BERT (SBERT) to perform sentence embedding and topic modeling processes to improve the summarization technique2. 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 recognition2. It is also necessary to refine the parameter tuning procedure to find a more precise combination of parameters.

Problem Statement

Technical | Functional

- Manually selecting the most pertinent applicants from a lengthy list of potential candidates is difficult.
- Finding people who fit a given job profile is a vital task for the majority of firms. As online hiring becomes more common, traditional hiring methods become less successful.
- Finding the most pertinent multilingual candidates through the manual hiring process is therefore one of the most important issues in multilingual job offers and resumes.
- In order to facilitate job seekers' access to recruitment opportunities and lessen the amount of human labour involved in the hiring process, an automatic recruiting system is necessary.
- To solve the challenge of finding the right candidate out of hundred resumes, this project explores to build a resume shortlisting and ranking with Transformers.

Project Objectives

Primary & Secondary Objectives | Expected Outcome

The three objectives of this study are;

- ☐ Collect the resumes as per the defined JD

The resumes are collected by HR from online job platforms, Referrals from existing employees, and third-party consultancies. But getting the exact JD related resumes are challenging For this project collected around two hundred resumes.

- ☐ Build a custom algorithm to shortlist the resume as per the JD given

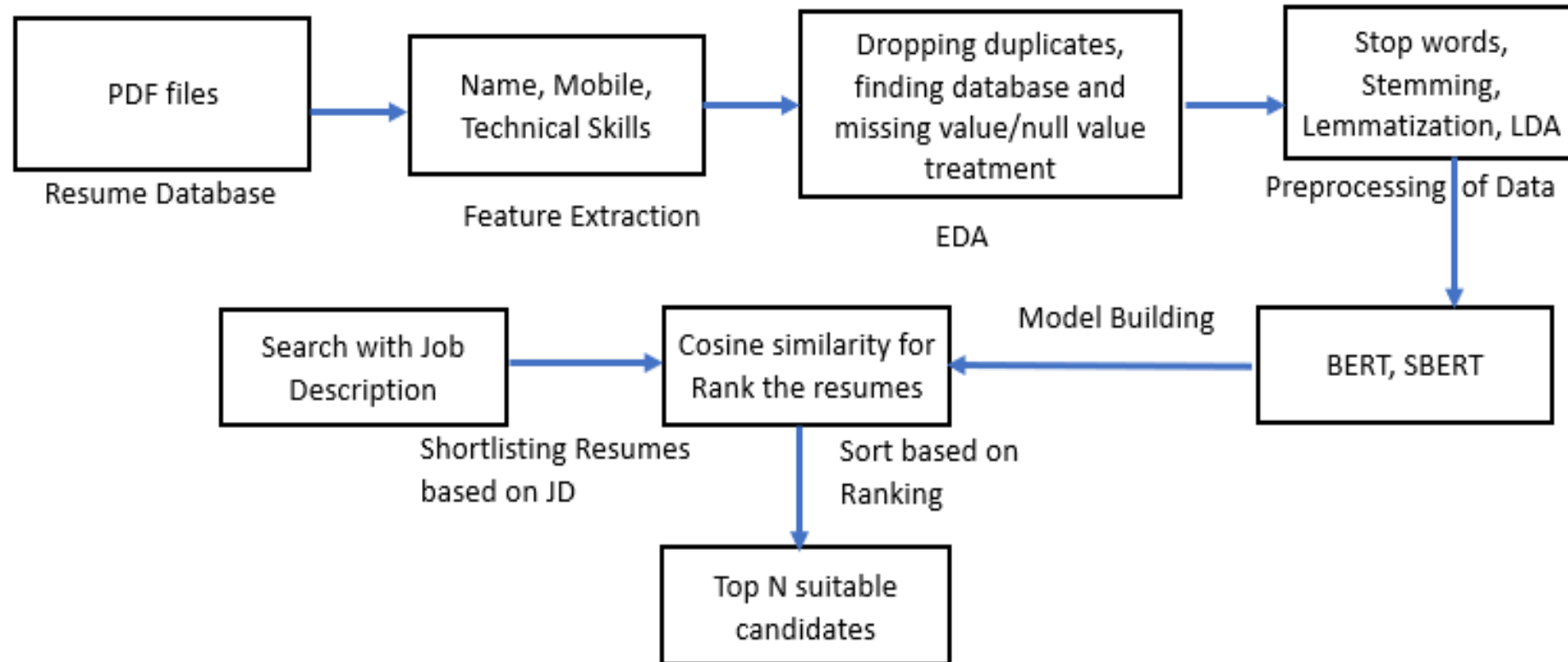
Once the ResumeParser extracts the skills to pandas. Based on the JD provided by HR the resumes matches will be shortlisted and moved to a list.

- ☐ Create a ranking algorithm to get the best out of shortlisted resumes.

With the help of cosine similarity and SBERT model, the project ranks the resumes

Project Methodology

Conceptual Framework | Research Design



Resource Specifications

Software | Hardware | Others

☐ NLTK

☐ ResumeParser is used for the extraction of required data like Name, Mobile Number, Email Address, Skills.

☐ EDA

Step 1: Divide the text into words.

Step 2: Eliminate all punctuation and symbols and, if desired, lowercase all words.

Step 3: Eliminate the stop words.

Step 4: Use the Snowball Stemming Algorithm to stem the words.

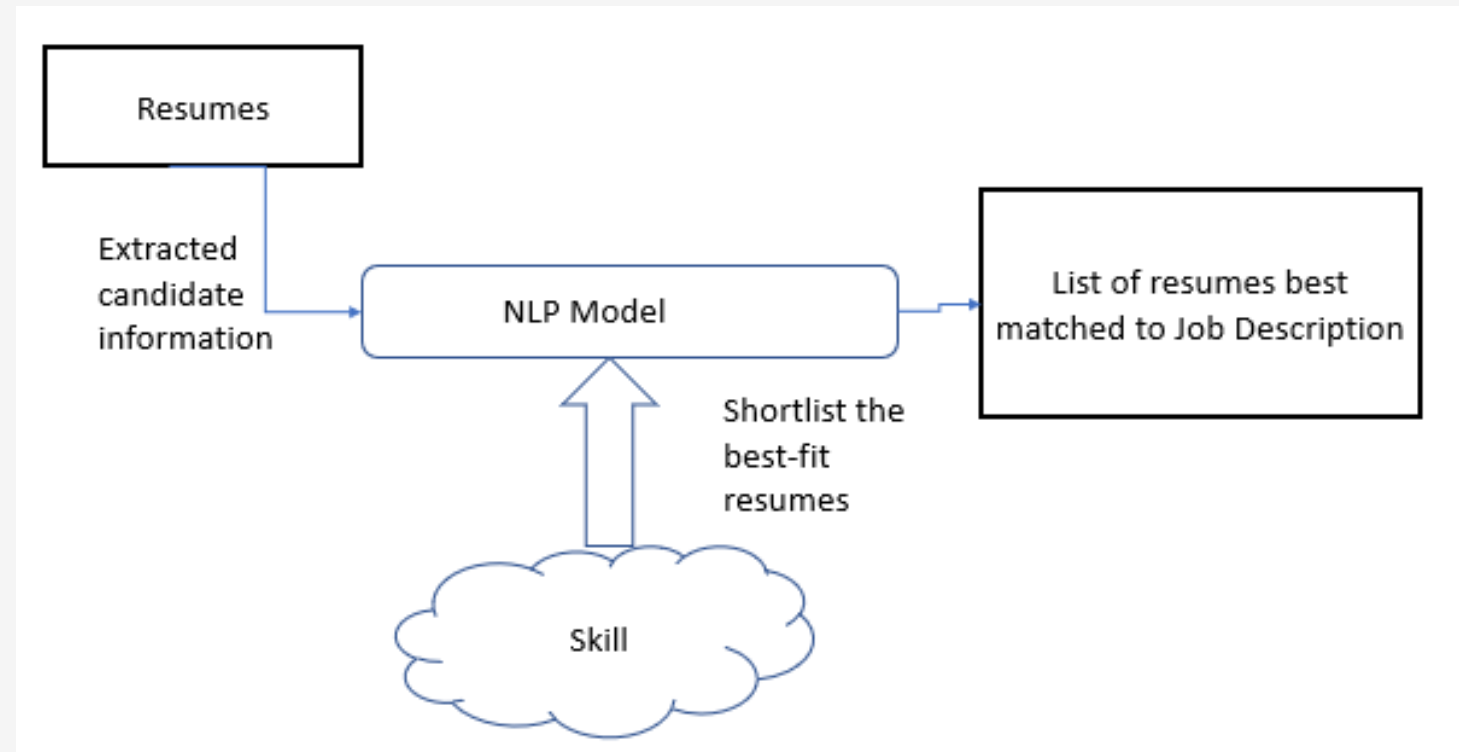
Step 5: Add parenthesis to each word before adding the field names (if appropriate).

☐ Encoding: BERT and SBERT

☐ Cosine similarity with the job description

The suggested model will be required the below inputs:

1. Resumes
2. Job description



Two hundred resumes were collected as part of data sets. SBERT for the STS task, permits two steps in the prediction of similarity:

Step: (1) First, using a sentence encoder, obtain sentence embeddings for each sentence.

Step: (2) Next, as the model-predicted similarity SBERT and BERT, compute the cosine similarity between the two embeddings of the input sentence pair.

Testing and Validation

Test Results | Learnings

More specifically, it find that the sentence embedding that outperforms the Classical Least Squares (CLS) vector is obtained by averaging over the SBERT context embeddings in the final 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.

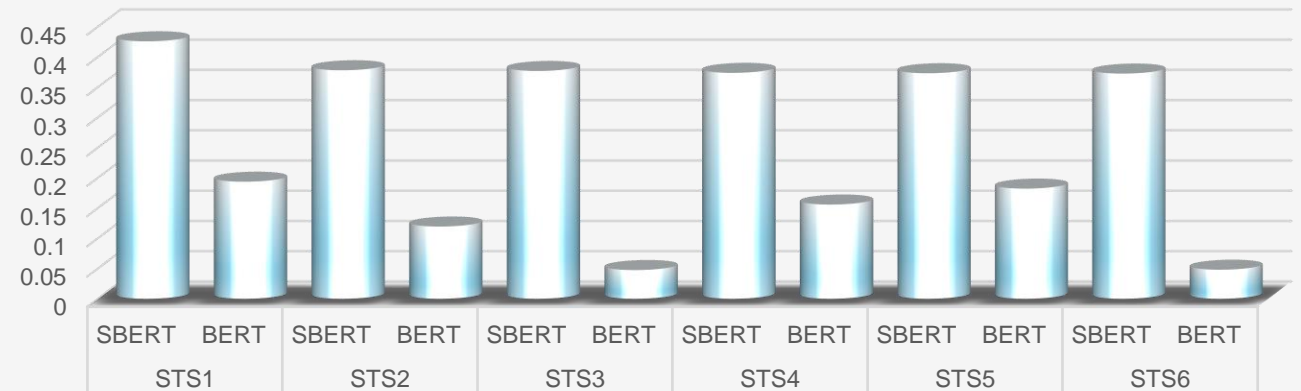
Analysis and Results

Key Findings | Insights

SBERT performs better than the BERT in terms of correlation.

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



Suggestions and Conclusion

Insights | Next Step | Future Scope

- The Proposed SBERT transform helps recruiters screen resumes more quickly and effectively, cutting the cost of hiring. As a result, the business will have access to a possible applicant, who will then be successfully put in a company that values his or her abilities and skill set.
- This method evaluates candidates' skills and ranks them in accordance with the job description and skill requirements of the employing organization. To provide a fast overview of each candidate's qualifications, a summary of their resume is supplied.
- The usage of Artificial Intelligence techniques or any other effective sentence embedding transformers will be made for further improvement.

References

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1. Vaswani, Ashish, et al. "Attention is all you need." Advances in neural information processing systems 30 (2017).
2. González, José Ángel, Lluís-F.Hurtado, and FerranPla. "Transformer based contextualization of pre-trained word embeddings for irony detection in Twitter." Information Processing & Management 57.4 (2020): 102262.
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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



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Annexure

Additional Information | Plagiarism score

Resume Shortlisting and Ranking with Transformers

ORIGINALITY REPORT

13%

SIMILARITY INDEX

5%

INTERNET SOURCES

10%

PUBLICATIONS

3%

STUDENT PAPERS



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*Thank
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