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An Abstractive Text Summarization using Decoder Attention with Pointer Network

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Abstract*: In contemporary times, an abundance of unstructured data prevails across social media and the web. Text summarization, a process aimed at distilling relevant information concisely without altering its core meaning, has become crucial. Manual text summarization is resource-intensive, prompting the exploration of automated methods. While deep learning algorithms, particularly in abstractive text summarization, have gained popularity, further research is needed to understand their integration with semantic-based or structure-based approaches.*

This research leverages a dataset of 1,735 resumes sourced from Kaggle to propose a novel framework. The framework combines semantic data transformations and deep learning approaches to enhance abstractive text summarization. A key focus is addressing the challenge of handling unregistered words. The proposed solution, Decoder Attention with Pointer Network (DA-PN), is introduced. DA-PN incorporates a coverage mechanism to mitigate word repetition in generated text summaries, thereby improving the quality of summaries. The method aims to safeguard against the propagation of errors in generated text summaries. The performance of the proposed approach is evaluated using the Recall Oriented Understudy for Gisting Evaluation (ROUGE) indicator. Notably, the proposed method achieves an average ROUGE score of 26.28, surpassing existing methods. The emphasis on combining semantic data transformations, deep learning, and addressing specific challenges like word repetition sets this research apart in the field of abstractive text summarization.

Keywords: Abstractive Text Summarization, Decoder Attention, Deep Learning, Pointer Network, Recall Oriented Understudy for Gisting Evaluation (ROUGE).

I. INTRODUCTION

Over the last decade, the landscape of job recruitment has undergone a significant transformation with the advent of online enrolment platforms such as Naukri.com, Boss, Indeed Hiring, Glassdoor, Monster, LinkedIn, and Zhaopin. These platforms have not only streamlined the hiring process but have fundamentally revolutionized how job seekers connect with potential employers[1]. This paper delves into an innovative approach to job suggestions, recognizing the evolving needs of both job seekers and recruiters in this dynamic digital era[2].

The proposed system sets out to optimize the job-matching process by extracting job offers from sa.indeed.com and subjecting them to a series of pre-processing, training, and matching procedures[3]. The ultimate goal is to facilitate recruiters in identifying the most suitable candidates for specific job positions while simultaneously providing job seekers with relevant opportunities closely aligned with their professional profiles.

Beyond the technicalities of the proposed system, the paper places emphasis on the broader societal aspect of job creation, specifically targeting individuals with disabilities. Despite facing disproportionately challenging situations in the job market, this marginalized group is at the forefront of the discussion. Hiring a suitable candidate can be difficult for many organisations because they need to meet certain requirements listed in the job description. A system utilising Artificial Intelligence is designed to assess and forecast a qualified applicant from a database of candidate resumes that is accessible[4]. The paper advocates for a shift in perspective within companies, urging them to focus not solely on the challenges faced by people with disabilities, such as those with autism, but rather on creating an inclusive environment that accommodates diverse strengths and enables success.

Within the field of natural language processing (NLP), text summarising is a crucial activity that aims to reduce large amounts of textual data into brief yet meaningful summaries. In particular, abstractive summarization aims to provide unique, coherent summaries that resemble material created by humans rather than just extracting text fragments from existing sources.To examine the most important recruitment parameters, a resume parser has been developed using natural language processing (NLP). Later, a strong tool for resume matching based on job criteria was created by utilising the candidate's pie chart display capability in the algorithmic structure of the parser[5].

The method investigated in this paper, called "Abstractive Text Summarization using Decoder Attention with Pointer Network," offers a novel technique intended to deal with the difficulties involved in text summarization. This approach combines important NLP techniques with the Pointer Network framework's Decoder Attention mechanism to provide a precise and sophisticated abstractive summarization process.

The contributions of this work are multifaceted. It introduces the DA-PN model, a sophisticated mechanism that integrates attention distribution, a coverage mechanism, and mixed learning objectives. This model seeks to address intricacies in text summarization, such as handling unregistered words and preventing word repetition in generated text summaries. By combining various learning objectives and implementing a self-critical gradient algorithm, the proposed DA-PN model aims to enhance the overall quality of text summaries.

As the paper unfolds, subsequent sections promise a more in-depth exploration. A literature review is poised to provide insights into existing research and methodologies, offering a foundation for the proposed method. Section 3 will intricately detail the workings of the proposed system, shedding light on its intricacies. The paper then plans to present results and conduct a comparative analysis, evaluating the effectiveness of the proposed model against existing methods. Finally, the conclusion will encapsulate the key findings and contributions, potentially offering insights for future research in the dynamic intersection of job recruitment, technology, and societal inclusivity.

In exploring the difficulties with conventional summarising methods, the study highlights the need for more advanced strategies that go beyond simple extractive methods. Through the integration of the Decoder Attention mechanism into the Pointer Network, this study seeks to close the gap between extractive and abstractive summarising, providing a new and efficient method for producing thorough and contextually rich summaries from extensive textual sources.The work aims to provide a contribution to the field of abstractive summarization and NLP approaches by means of this inquiry.

II. LITERATURE REVIEW

The literature review offers a thorough summary of many research in the field of employment recommendation systems, including a diverse range of viewpoints and approaches. Every study offers unique approaches and improvements that make a substantial contribution to the improvement of job recommendation systems. It review delves into several studies focusing on job recommendation systems, offering diverse perspectives and methodologies. Shao et al. conducted an extensive exploration of in EXIT, proposing a model that utilizes linguistic spaces for attribute encoding. This model introduces matching layers to gauge the degree of alignment between job posts and resumes, enhancing online recruitment processes. Ong and Lim presented an information-driven approach for professional vision, emphasizing skill recommendations through word embedding and a feed-forward neural network. Their method aims to align job titles with job skills, enhancing accuracy and F1-score[6]. Yang et al. explored a hybrid content and filtering approach, incorporating cost-sensitive informative relational learning for job recommendations. This approach allows for modulation between recall and precision, addressing challenges related to big-data-scale systems.

In the area of professional skill suggestions, Ong and Lim's information-driven method represents a forward-thinking perspective. Their algorithm seeks to match job titles with particular skill suggestions by utilising feed-forward neural networks and word embedding, which improves accuracy and F1-score metrics that are important for efficient job matching.

One noteworthy feature of Yang et al.'s hybrid content and filtering strategy is the incorporation of informative relational learning that is sensitive to cost[7]. This invention offers a customisable approach that strikes a compromise between precision and recall, two important factors in job suggestions, in addition to addressing the scalability issues in big-data-scale systems.

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The NLP-powered bidirectional recommendation system developed by Alsaif et al. demonstrates a comprehensive strategy that is advantageous to recruiters and job seekers alike. Their research emphasises the benefits that both job seekers and employers receive from NLP models, even if it also recognises the difficulties associated with personalisation in these models.

Yildirim et al. focused on overcoming the issue of information scarcity in network correspondence, introducing a machine for reciprocal suggestion based on multiple-objective deep factorization. Their approach outperformed traditional methods, achieving faster processing times. Alsaif et al. introduced a bidirectional recommendation system based on Natural Language Processing (NLP) for job seekers and recruiters[8]. This system not only serves recruiters in identifying suitable candidates but also aids job seekers in finding relevant job opportunities. The study acknowledges the lack of personalization in NLP-related suggestion models but emphasizes the mutual benefits for both parties.

Jain et al. implemented an Applicant Tracking System (ATS) for the Hindi language, utilizing a Real Coded Genetic Algorithm (RCGA). Their rigorous experimentation evaluated different feature groups, highlighting the significance of named sentence similarity and named entity features. However, challenges were noted in terms of cost efficiency and broader acceptance of ATS for HR solutions.

Sethi et al. presented a transformer-based method for generating improved summary averages, combining Bart and T5 methods. Their study compared the effectiveness of these approaches, with Bart outperforming T5 in various aspects[9]. While the method demonstrated efficiency and relevance in content summarization, limitations were acknowledged, such as reliance on a limited dataset and potential cost considerations.

In essence, each study contributes valuable insights into the realm of job recommendation systems, addressing specific challenges and proposing innovative solutions. These diverse approaches collectively contribute to advancing the understanding and effectiveness of job recommendation systems in different contexts and scenarios.

III. PROPOSED METHODOLOGY

The research meticulously navigates through various stages aimed at optimizing job recommendation systems, with a primary focus on data collection, integration, and pre-processing for efficient job matching. The chosen dataset comprises 1,735 resumes obtained from Kaggle, each containing diverse fields such as resume title, location, role description, technical skills, education, certification, and additional details. Additionally, four distinct job descriptions related to Machine Learning Data Scientist, Full stack, Java, and Python developer were sourced from LinkedIn, contributing to a comprehensive dataset for analysis.

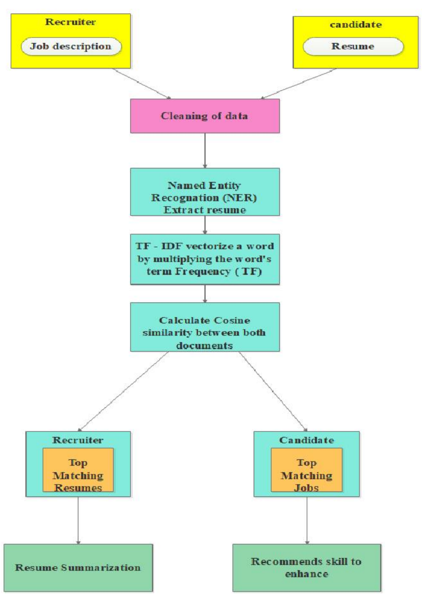

Fig1. Workflow of bidirectional system

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The suggested approach presents a bidirectional system that provides recruiters and workers with the best suggestions. Named Entity Recognition and data cleansing are used to retrieve important information from resumes. Using the cosine similarity metric, resumes are evaluated for how close they are to job descriptions. Pre-processing of data is done by NLP approaches, and resumes and text are summarised using the DA-PN+Cover+MLO method. The model that is suggested in this study is shown Above.

Data Collection and Integration

The 1,735 resumes in the resume dataset used in this study were obtained from Kaggle. The dataset includes profiles with several variables, including job description, location, resume title, technical abilities, education, certifications, and other information. Four Job Descriptions (JDs) from LinkedIn are also included in the study; these JDs are centred around positions such as Machine Learning Data Scientist, Full Stack Developer, Java Developer, and Python Developer. Job titles, business names, localities, descriptions, necessary academic requirements, and desired abilities are all included in these JDs.

Pre-processing

As the first stage of data preparation, pre-processing entails a number of critical activities that transform unstructured data into a structured format.Text summarization automatically creates a summary from the original document that includes all pertinent and significant information in key sentences. Looking at the summary results, extractive and abstractive methods are among the primary strategies[10]. This stage involves matching job descriptions to a database of pre-loaded resumes and evaluating applicant resumes in return against a variety of job descriptions that are already in the system. By using Natural Language Processing (NLP) techniques, data purification is used to retrieve important information. Symbols or numerical values that are not necessary for the program's needs are frequently seen in resumes and job descriptions. Consequently, these superfluous characters—which include punctuation, stop words, and numbers—are methodically eliminated in order to expedite the processing of resumes and job descriptions. In order to guarantee uniformity and consistency in the data format for future analysis, all textual components are also changed to lowercase.

Named Entity Recognition (NER)

applications sometimes include extraneous information that may not correspond with a recruiter's particular needs, which makes it difficult to go through a large number of applications. This procedure is streamlined by using the Named Entity Recognition (NER) paradigm, which enables quick resume evaluations. The time and effort required to choose a small list of applicants from a big resume pool is greatly decreased by this technique. An rapid overview of resumes is made possible using the NER model, which also makes it feasible to extract important things like as names, talents, educational histories, and other crucial information.It is predicated on the theory that organisations are becoming closer to the ideal of sustainable development as a result of the digitization of work and human resources procedures. In this context, sustainability refers to upholding a balance among social, environmental, and economic factors[11]. This automated method makes it easier to provide succinct summaries, which improves the effectiveness of the procedures involved in evaluating and selecting candidates.

Generating Vectors

Recruiters often receive a large number of resumes with extraneous information that does not correspond to their needs, which makes it difficult to sort through them all. This procedure is made more efficient by using the Named Entity Recognition (NER) paradigm, which enables quick resume evaluations. The work required to narrow down prospects from a big resume pool is greatly decreased by this technique. Key elements such as names, talents, educational histories, and other important information may be extracted from resumes instantly with the use of the NER model. Candidate evaluation and selection procedures are made more efficient by this automated method, which makes it easier to provide succinct summaries.The Logarithmic factor in the TF-IDF equation (3) serves the mathematical purpose of assigning low TF-IDF values to words that are either overly common or excessively rare in the corpus. TF-

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IDF values a word by multiplying the word's Term Frequency (TF) equation (1) with the Inverse Document Frequency (IDF) equation (2).

$$TF = \frac{No.\,of\,times\,the\,term\,appears\,in\,a\,document}{Total\,no.of\,terms\,in\,the\,document} \quad (1)$$

$$IDF = \log log\left(\frac{No.\,of\,documents\,in\,the\,corpus}{No.\,of\,documents\,in\,the\,corpus\,that\,contains\,the\,term}\right) \quad (2)$$

$$TF - IDF = TF * IDF \quad (3)$$

Words of enormous relevance in the corpus are given higher scores by the TF-IDF scoring algorithm, whereas words with lesser significance are given lower ratings. The fact that Doc2Vec can understand full texts rather than just words makes it an effective tool for teaching purposes. Doc2Vec provides n-Dimensional vector generation with two important features: contextual similarity for more expressive and subtle representations and efficient dimensionality reduction for streamlined representation. This conversion gives the model the ability to represent both reduced dimensions and extensive context, which improves its ability to grasp subtle language correlations in the dataset.

Cosine Similarity

Prior to measuring the similarity or distance, it is necessary to comprehend that the research objects are samples, and that the measurement of their constituent parts is done as features. Two data samples for the proposed analysis are the job description and the candidate's résumé. Two dimensions can be used to represent two features, and samples can be visualised using the Cartesian coordinate system. Of course, if there are three characteristics, samples may also be seen in three dimensions. No matter how many characteristics or dimensions there are, the distance will always be calculated in the same way. The method for measuring distances varies depending on the specific workplace.The particular scenario determines which distance measurement method is best. The Euclidean distance, for example, is useful in several situations where distances between observations need to be calculated. On the other hand, in certain situations, more complex techniques like the cosine distance could be required. Documents are ranked according to cosine similarity, a metric that is used to measure similarities between them regardless of size. Instead, then concentrating on the precise separation between two points in space, it emphasises their direction. This method prioritises the spatial alignment of documents above their exact closeness in space, enabling a more nuanced evaluation of their similarities.This means that cosine distance is less affected by magnitude or how large the given numbers are [6].Assume x & y is 2 sample vectors for comparison. The relation for calculating the analogy of cosine is given as equation (4):

$$os_{sinsin\,(x,y)} = \frac{x,y}{||x||\bullet||y||} \quad (4)$$

$||x||$ represents Euclidean norm of the vector $x = (x_1, x_2, x_3, \ldots\ldots, x_p)$, defined as equation (5):

$$\sqrt{x_1^2 + x_2^2 + x_3^2 + \ldots + x_p^2} \quad (5)$$

Likewise, $||y||$ represents the Euclidean norm of the vector y.

The angle between vectors x and y is measured using the cosine computation. When the vectors are 90 degrees apart and perpendicular, there is no resemblance, as shown by a value of 0. On the other hand, a number nearer 1 indicates a lower angle of alignment between the two vectors, indicating a higher degree of resemblance. Higher values indicate a more parallel orientation and, thus, a greater match. This numerical representation clearly illustrates the degree of alignment or agreement between the vectors.

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Summarization

Out-of-vocabulary (OOV) words are handled efficiently by combining a Decoder Attention (DA) technique with a Pointer Network (PN). By merging the context vectors produced by the original text and the decoder, this fusion enables the simultaneous control of a subset of the real text and extra vocabulary. Furthermore, a multiple-attention coverage method is used to lessen worries about word repetition. To provide a varied and non-repetitive word selection, this method continually uses coverage vectors from the encoder and decoder, altering attention weight.An input-to-input mapping layer receives the attention data from the decoder in order to handle word repetition. Because of this configuration, the model may concentrate on historical data, which reduces word repetition. Additionally, a Mixed Learning Objective (MLO) function is used to improve the readability of output text summaries. This method improves the overall readability of the output text summaries by augmenting some discrete gradients during scoring and setting a global reward. This all-inclusive approach seeks to maximise content creation while maintaining consistency and reducing duplication.

DA-PN Method

The DA-PN approach combines Decoder Attention (DA) with the Pointer Network (PN) architecture to address the problem of unregistered words. Choosing whether to keep an unregistered word from the source text or replace it with an existing word from the fundamental vocabulary is one of the decisions that this approach faces at each level. Two separate steps are involved in this decision-making process: first, unregistered words from the original text are copied using softmax with normalised probability, and then words are predicted from the input data by utilising the decoder attention distribution. The DA-PN model successfully predicts the occurrence of unregistered terms inside the real text by combining these methods without adding them to the core vocabulary. This paradigm is notable for having two input layers, each of which represents a word, making it easier to copy words from the fundamental vocabulary or the real text. Incorporating pgen, a switching mechanism, produces probabilities that facilitate efficient input management.

Moreover, the attention mechanism of the decoder makes up for the data deterioration brought on by long sequences. This compensation makes it possible for the model to pinpoint important data points more precisely, which improves its overall performance in text prediction optimisation and managing unregistered words.The distribution of attention regarding to possibility distribution of every word in actual text can be calculated as equation (6).

$$\alpha^{t} = softmax\left(V_{\alpha} \tan tan\, h \left(W_{\alpha} s_{t}^{T}\right)\right) \tag{6}$$

Where, W and V represents parameters of weight and st represents the decoder's hidden layer state at time stage t. The sum of weighted attention distribution acquired from equation (6) and the decoder stage before the present time step represents the context vector of the final decoder as equation (7)

$$u_{t}^{d} = \sum_{j=1}^{t-1} \alpha_{j}^{t} s_{j} \tag{7}$$

The possibility of the switch pgen could depend on the decoder/ encoder context vector with the real invisible-layer condition, as equation (8)

$$p_{gen} = \sigma\left(W_{y} y_{j-1} + W_{e} u_{t}^{e} + W_{d} u_{t}^{d} + bt_{ptr}\right) \tag{8}$$

Where, Wy represents a matrix of the weight of the prior word yj-1, We and Wd represents a matrix of weight of the encoder and decoder hidden state at the present stage respectively, ute represents the context vector of the last encoder, utd represents the context vector of the final decoder, and btptr represents bias. Bias and weight matrix in equation (8) are the parameters that can added during the iteration of model training. The linear weight adds those parameters that are processed by the sigmoid function and marked between 0 and 1 as a soft switch for managing the input layer source, based on data of 2 stages namely source text and vocabulary. The distribution of vocabulary of the present time step is described as equation (9)

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$$P_{vocab} = Softmax\left(V^{'}\left(V\left[s_t, w\right] + bt\right) + bt^{'}\right) \tag{9}$$

Where, st represents a sequence of the present state, V represents the weight matrix, bt represents bias for iteration in training and w represents the word that is predicted. The possibility of the last prediction for word w is represented as equation (10)

$$P_{final}(w) = p_{gen} P_{vocab}(w) + \left(1 - p_{gen}\right) \sum_{i:w_i = w} a_i \tag{10}$$

Where, p_{gen} represents the possibility of managing input value, $P_{vocab}(w)$ represents the word distribution in the last outcome vocabulary and ∑shows the context vector of the encoder.

Results

The experimental setup is described in detail in this part, together with quantitative and qualitative assessments, a comparative study, and debates and conclusions about the suggested technique. Along with suggesting alternate jobs to candidates, this study also suggests machine learning algorithms that shortlist candidates for the desired job role by utilising user context information[12]. It provides a thorough analysis of the experimental design, evaluates the methodology's performance using both quantitative and qualitative methods, does comparison analyses, and has in-depth discussions and closing remarks.

Experimental Setup

The suggested model is simulated in this study using the MATLAB (2022a) environment, which has the following system requirements: 16 GB of RAM, an Intel Core i7 processor, and Windows 11 (64 bit). The evaluation indicator ROUGE, a software programme that assesses the automated summarising process, is used to quantify the effectiveness of the suggested approach. The suggested method's performance on the LCSTS dataset is shown in Table 1. The assessment makes use of the evaluation indication. The two baseline techniques are used in the DA-PN assessment. Compared to baseline approaches, which achieve an average of 21.53, the suggested DA-PN achieved an average of 26.73. The ROUGE-1, ROUGE-2, ROUGE-L, and average of the ROUGE assessment indicators.To assess how well the suggested approach performs, the evaluation indicators ROUGE-1, ROUGE-2, ROUGE-L, and an average of the ROUGE are used. According to Table 1, the suggested approach outperforms the alternatives in terms of performance.

Table 2. Performance of proposed method in LCSTS data

Models	ROUGE-1	ROUGE-2	ROUGE-L	ROUGE - AVG
'Bi-LSTM + Attention' (baseline)	26.47	9.09	29.03	21.53
'Seq2Seq + Attention' (baseline)	28.14	10.01	30.89	23.01
'DA-PN'	32.16	13.49	31.28	25.64

The performance of the suggested technique using the TT News Corpus dataset is shown in Table 2. The assessment makes use of the evaluation indication. Compared to baseline approaches, which achieve an average of 22.53, the suggested DA-PN achieved an average of 26.28. To assess how well the suggested approach performs, the evaluation indicators ROUGE-1, ROUGE-2, ROUGE-L, and an average of the ROUGE are used. According to Table 3, the suggested approach performs better than the others.

Table 2. Performance of proposed method in TTnews Corpus dataset

Models	ROUGE-1	ROUGE-2	ROUGE-L	ROUGE - AVG
'Bi-LSTM + Attention' (baseline)	26.48	9.23	28.43	21.38
'Seq2Seq + Attention' (baseline)	28.27	9.31	30.03	22.53
'DA-PN'	32.45	13.85	30.95	26.28

The performance of the suggested technique using the Kaggle dataset is shown in Table 3. The average score of 33.42 achieved by the suggested DA-PN is higher than that of baseline approaches, which score 26.17. For the assessment, the ROUGE-1, ROUGE-2, ROUGE-L, and average of the ROUGE are used as evaluation indicators. Table 4 indicates that the suggested approach performs better than the other approaches.

Models	ROUGE-1	ROUGE-2	ROUGE-L	ROUGE - AVG
'Bi-LSTM + Attention' (baseline)	26.17	9.43	30.44	22.01
'Seq2Seq + Attention' (baseline)	28.57	10.43	31.36	23.45
'DA-PN'	33.42	13.96	31.86	26.30

Table 3. Performance of the proposed method in Kaggle dataset

From the results mentioned above, it is clear that the proposed DA-PN method outperforms existing methods and protects against the spread of increasing errors in generated text summaries.

Comparative Analysis

Table 4 describes the comparative study of the suggested technique. The suggested approach is contrasted with other approaches already in use, such as ATS [14] and TF [15], both of which use the Kaggle dataset. The evaluation indicators ROUGE 1 and 2 are used for the comparison; the suggested technique yields relative improvements over the current methods, showing 1.92 in ROUGE – 1 and 0.81 in ROUGE – 2.

Table 4. Represents the Comparative analysis

Methods	Dataset	ROUGE - 1	ROUGE -2
Jain et al. [14]		0.79	0.66
Sethi et al. [15]	Kaggle	1.5	-
Proposed Method		1.92	0.81

IV. CONCLUSION

In conclusion, the escalating demand for online recruitment necessitates a departure from conventional hiring practices. Relying solely on traditional methods proves inadequate in the face of this evolving landscape, especially when it comes to the challenges of validating resumes online and the susceptibility to manual errors inherent in such processes.

The bidirectional approach presented in this study leverages Named Entity Recognition (NER) to proficiently extract pertinent information from resumes. Additionally, the utilization of cosine similarity provides a quantitative measure of the alignment between job requirements and resumes, offering a comprehensive evaluation from both perspectives. Notably, the Decoder Attention (DA) mechanism, incorporating the Pointer Network (PN) as DA-PN, addresses the critical issue of unregistered words, fortifying the system against potential errors.

The decision to employ DA-PN is strategic, as it effectively safeguards against the propagation of errors in the generated text summaries. Performance analysis conducted in this study demonstrates that the proposed method outperforms alternative approaches. This not only underscores the method's efficacy but also positions it as a promising solution for the challenges posed by online recruitment.

Intentionally using DA-PN serves as a safeguard, reducing the likelihood of mistakes in text summaries that are produced. Performance assessments show that this strategy works better than other alternatives, confirming its effectiveness and promise as a fix for problems with online recruiting.Prospective investigations need to concentrate on improving abstractive summary methods to enhance recruitment procedures, enabling more complex and situation-specific evaluations. The basis of bidirectional extraction and attention processes identified in this work opens the door for future advancements in online recruitment tactics. Continuous attempts to improve summary approaches will be crucial in influencing future hiring practices and guaranteeing the effectiveness and precision of applicant evaluation in online recruiting as the environment changes.

Looking ahead, future research should focus on advancing abstractive summarization techniques. This emphasis aims to elevate the overall quality of hiring processes by enabling more nuanced and context-aware assessments. The proposed method, with its foundation in bidirectional extraction and attention mechanisms, lays the groundwork for continued innovations in online recruitment strategies. As the landscape evolves, ongoing efforts to enhance summarization techniques will play a pivotal role in shaping the future of hiring practices.

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