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(CMSE11427) WEB AND SOCIAL NETWORK ANALYTICS

STRATEGIC INSIGHTS: RECRUITMENT, MARKETING, AND ADVERTISEMENT ANALYTICS

B238121

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1. **RECRUITMENT REVOLUTION: UNLEASHING RECOMMENDER SYSTEMS**

Recommender systems (RSs) are information filtering systems (Van Meteren and Van Someren, 2000) that in recruitment domain are used by both job seekers and candidate recommenders. Common approaches to analyze similarities and provide recommendations based on preferences are collaborative filtering (CF) and content-based filtering (CBF). Here, CBF is used as the primary recommendation technique for candidate-job matching, emphasizing its capacity to provide personalized recommendations tailored to individual candidate profiles and job attributes, assisting in efficiently matching candidates to appropriate job opportunities. Additionally, CBF's transparency and resilience against the cold-start problem make it particularly suitable for scenarios where new job listings are frequent and historical interaction data may be limited.

CBF models, like **Profile-Based Recommendation Systems** (PRES), recommend items by comparing user profiles with item content, which are represented using terms extracted from documents. It then undergoes parsing and is reduced to terms. For user profiles, terms represent documents that users find interesting, determined through explicit or implicit feedback. Then, correlation between item content and user preferences is calculated. It classifies items into positive or negative classes based on this correlation, utilizing a function learned from training data to make recommendations (*Fig. 1*).

Thus, CBF provides a sophisticated approach to recommendation systems, leveraging semantic analysis and utility matrices for precise matching. This not only enhances the accuracy of candidate-job alignments but also aids HR professionals in streamlining their recruitment processes by offering tailored recommendations that align closely with job requirements and candidate profiles. However, challenges may arise from the need for extensive cross-sector testing and the potential limitations of dataset diversity, requiring careful consideration to ensure robust and equitable recruitment outcomes. Moreover, ethical scrutiny is paramount to address biases in profile matching, reinforcing the importance of transparency and fairness in recruitment processes.

*Fig. 1-CBF Process Flowchart*

Algorithmic biases in RSs can perpetuate discrimination in hiring, violating non-discrimination laws (Kumar et al., 2023). It can manifest in gender pay gaps, stereotypical job perceptions, or preferences towards certain characteristics in candidates. For instance, it can systematically favour candidates from certain demographic groups, which inadvertently perpetuates gender or racial disparities in employment outcomes. This not only undermines the principles of equal opportunity and merit-based selection but also reinforces existing social inequalities hindering diversity and social mobility. To mitigate these ethical concerns, RSs developers must prioritize fairness by regularly auditing algorithms for biases, diversifying training data, and implementing transparency measures. Additionally, promoting awareness and education among employers and users about potential biases can help challenge preconceived notions and foster more inclusive hiring practices, thus safeguarding against legal consequences and promoting diversity and social mobility.

1. **NAVIGATING INFLUENCER MARKETING STRATEGIES**

Influencer marketing on social media is becoming vital for growth strategies to establish businesses. Numerous Social Network Analysis (SNA) approaches have emerged to assist in this endeavour. A ‘similar item’ recommendation system like Reel.com’s Movie Matcher (Schafer, Konstan & Riedl, 1999) based on user’s search history or interest leads customers to utilize ‘browsing functionality’ to explore content without extensive searching. Moreover, email notifications keep customers updated about product launches, while personalized recommendation lists tailored to user preferences drive engagement and sales. Additionally, integrating user-generated content such as comments and ratings fosters trust and authenticity within the community (*Fig.2*). However, the real challenge is identifying the impactful influencers who can amplify brand messaging effectively.

A cartoon of a person with his hands out

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To gauge an influencer's effectiveness and tackle the undesirable effect of an 'echo chamber’ where existing customers dominate brand exposure, a strategic approach could be implemented. Analyze the influencer's degree of ‘**centrality**’ within the social network, to measure the number of connections. Influencers with a high degree centrality enable targeted dissemination of promotional content, maximizing exposure to a wider audience. Also, ‘**betweenness centrality’**

*Fig. 2 – Marketing Strategies (Source: Internet)*

identifies influencers who act as bridges between different segments of the network, facilitating connection with new customers. Additionally, ‘**authority metric’** measures an influencer's expertise and credibility within specific domains bolstering the persuasiveness of promotional messages. Finally, examining the ‘**engagement rate**’ of potential influencers offers valuable insights into their ability to resonate with their audience and drive meaningful interactions, indicative of their potential to influence purchasing decisions.

However, relying solely on these metrics can be limiting and potentially misleading. Degree centrality may not accurately capture depth of engagement or quality of connections as, an influencer with large followers may have superficial connections, leading to lower effectiveness in driving desired actions. Similarly, influencers with high betweenness centrality, might not have significant influence within specific niche communities relevant to target audience. This limitation can result in overlooking influencers who possess strong resonance with their audience. Additionally, relying on authority metrics may overlook influencers who authentically resonate with their audience but do not have perceived authority. High engagement rates do not always translate into meaningful actions such as purchases. Moreover, it can be artificially inflated through tactics like engagement pods or fake followers, leading to misleading metrics. Therefore, a comprehensive approach that considers these metrics alongside qualitative assessments and contextual factors (*Fig. 3*) is necessary to accurately evaluate an influencer's suitability and effectiveness for marketing campaigns.

*Fig. 3 – Contextual Factors*

1. **WEB ANALYTICS MEASURES FOR HAGGISBUS ADVERTISEMENT CAMPAIGNS**

A colorful pie chart with text

Description automatically generatedIn the competitive nature of business, the efficacy of advertisements is paramount for long-term existence. This report leverages a dataset from HaggisBus, comprising 160,000 visitors, scrutinizing user behaviour by assessing advertisement efficiencies on LinkedIn, Facebook, and Partner websites, aiming to uncover performance differentials, offering insights to enhance campaign potency and drive business growth.

To assess the effectiveness, metrics such as bounce rate, conversion rate, and average visit duration were used. Results representing the percentage of visitors completing the desired action indicate variation in performance. For instance, the **'linkedin\_advert'** campaign exhibited a commendable conversion rate of 23.1% and a relatively low bounce rate of 74.8% (*Fig. 7*), indicating its effectiveness in driving user engagement and retention. In contrast, the **'facebook\_advert'** campaign struggled with a meager 0.9% conversion rate and an alarmingly high bounce rate of 99.07%, underscoring significant disparities in audience actions and campaign performance. Direct visits show the highest conversion rate of 29.1%, indicating a strong intent to engage or convert among users who directly typed the URL. However, the bounce rate for direct visits is relatively low at 68.33%, suggesting that these users are more likely to stay on the website and explore further. Similarly, users from Facebook shares and LinkedIn shares also exhibit low conversion rates and high bounce rates (*Fig. 4*). Therefore, users coming via adverts, especially from **LinkedIn**, demonstrate comparatively better performance in terms of engagement and conversion, while those coming via social media shares exhibit lower engagement and conversion rates. In addition to campaign analysis, user behaviour across different platforms unveiled intriguing insights.

*Fig. 4 – Conversion Rate by Source*

A graph of a bar chart

Description automatically generated with medium confidence**Android** users demonstrated moderate engagement levels with a bounce rate of 85.08% (Fig. 7) and a conversion rate of 14.92%, suggesting promising conversion potential among this audience segment. Conversely, **iOS** users exhibited higher bounce rates (87.31%) and lower conversion rates (12.69%), indicating diminished engagement and conversion propensity compared to Android users. **Windows** and **Mac** users displayed similar behaviour patterns, with bounce rates hovering around 83-84% and conversion rates approximately 16%. Interestingly, despite iOS users showing the highest total clicks, their conversion rates remained relatively lower compared to other platforms, hinting at potential barriers in the conversion for this A graph showing a comparison of conversion rate

Description automatically generateddemographic (*Fig. 5 & 8*). To complement the evaluation, the paths were evaluated, where **'blog\_1'** showed a higher conversion rate of 22.00% and a lower bounce rate of 78.00% compared to those with **'blog\_2'**, which had a conversion rate of 15.94% and a higher bounce rate of 84.06%, indicating varying levels of effectiveness in engaging and retaining visitors based on the content (*Fig. 6*).

*Fig. 5 – Comparison of Rates by Platform*

Therefore, users coming via **adverts**, especially from **LinkedIn**, demonstrate comparatively better performance in terms of engagement and conversion, while those coming via social media **shares** exhibit lower engagement and conversion rates.

*Fig. 6 – Comparison of Blog\_1 & Blog\_2 Rates*

In conclusion, the comprehensive analysis of advertisement effectiveness and user behaviour highlights the pivotal role of targeted campaigns and platform-specific strategies in optimizing engagement, thereby paving the way for sustained business growth and competitive advantage in the dynamic market landscape.

**GLOSSARY**

1. **Conversion Rate** – This determines the rate of web visitors who completed the desired action.
2. **Bounce Rate** - The percentage of users who deviate from the website after glancing at a page, indicating a lack of engagement.
3. **Average Time** **Duration** – The average amount of time a visitor spends on a website per session.

**REFERENCE**

Van Meteren, R. and Van Someren, M., 2000, May. Using content-based filtering for recommendation. In *Proceedings of the machine learning in the new information age: MLnet/ECML2000 workshop* (Vol. 30, pp. 47-56).

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**APPENDIX**

A graph showing a number of blue squares

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*Fig. 7 – Bounce Rate by Source*

A screen shot of a computer

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*Fig. 8 – Platform Comparisons*