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CMSE11427 Web and Social Network Analytics

Web Traffic and Social Network Analysis

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Recommender Systems

Recommender systems use unsupervised machine learning to personalize recommendations to users based on their preferences, behaviour, and interests. These systems work in two stages: generating candidate sets from a large amount of data, and ranking the generated sets to recommend items of interest (Resnick and Varian, 1997). Common methods for generating candidates include content-based and collaborative filtering recommendations. Other unsupervised techniques include clustering and dimensionality reduction. These methods group similar jobs or candidates together and reduce data dimensionality for easier analysis.

Applications in HR for Matching Candidates and Jobs

Recommender systems can suggest jobs to candidates based on their qualifications and preferences, or recommend candidates to employers based on job requirements. Clustering can group similar jobs or candidates based on shared characteristics such as job descriptions, requirements, or qualifications. Dimensionality reduction can reduce the number of variables in the data to make it easier to analyze and identify important variables for successful job-candidate matches. By applying these techniques, HR can improve the matching process, identify correlations between variables, and enhance the overall recruitment and hiring process.

Possible Benefits and Pitfalls

Unsupervised techniques, such as clustering, dimensionality reduction, and recommendation systems, can provide many benefits for the hiring process, including increased efficiency, accuracy, and personalized service. However, there are also potential pitfalls to be aware of. One challenge is the quality and quantity of data, which can greatly impact the accuracy of job-candidate matching. Another pitfall is the risk of over-reliance on algorithms, which may neglect essential factors that are not captured in the data. Lastly, there is a potential for discriminatory outcomes, especially if the data used to train the models reflects historical discrimination (Bobadilla *et al.*, 2013). It is crucial to monitor and evaluate these systems to ensure that they are equitable and unbiased.

Ethical Concerns and Potential Solutions

Recommender systems used in HR can be biased and unfair, leading to discrimination and social inequality. To combat these issues, the following solutions are suggested:

1. Diversity issues: The dataset should be diverse and include candidates and positions from a variety of groups. Algorithms should be designed to eliminate unfair bias and set diversity targets. The output should be monitored to ensure it does not reduce diversity (Helberger, Karppinen and D'Acunto, 2018).
2. Social mobility issues: Social mobility goals and designs should be incorporated into the algorithm, and the dataset should contain candidates and jobs from diverse backgrounds. The output of the algorithm should be monitored to ensure it does not exacerbate social inequality.

By addressing these ethical concerns and implementing these solutions, recommender systems can be designed to improve the job-candidate matching process and promote fairness and equality.

Social Media Network

Good Influencer

To identify potential social media influencers for RunTartan, it's important to consider metrics like reach, engagement, authority, and degree. Reach refers to an influencer's total number of followers, while engagement reflects the level of interaction an influencer receives on their social media posts. Authority refers to an influencer's level of expertise in a particular domain, and degree measures the number of connections an influencer has within their social network (Zhang, Moe and Schweidel, 2017). By analyzing data on potential influencers, RunTartan can identify those who have a high level of influence, credibility, and trustworthiness on social networks, and work with them to promote their products on social media. While a higher reach can mean a greater impact on marketing efforts, it's important to note that the number of followers is not necessarily the best indicator of influence due to fake followers and bot accounts.

Limitations of Each Indicator

When evaluating potential social media influencers for RunTartan, using a combination of metrics is important, rather than relying on any single metric. While metrics like reach, engagement, authority, degree, and betweenness can be helpful, they can also be limiting and potentially misleading if used in isolation. For example, an influencer with a large reach may have low engagement with their followers, and an influencer with high authority may not align with RunTartan's brand values (Dahnil *et al.*, 2014). It's also important to consider the quality of connections an influencer has and whether their followers are likely to be interested in RunTartan's products. By analyzing multiple metrics in the context of the brand's goals and values, RunTartan can identify the most effective influencers for promoting their products on social media.

Echo Chamber

RunTartan can address the issue of an "echo chamber" by collaborating with diverse influencers. Influencers with a broad follower base can help expand the brand's reach and increase brand awareness, although the message may not be as targeted to specific audiences. On the other hand, collaborating with niche-focused influencers can help the brand reach new customer groups who are interested in the specific niche that the influencer covers, leading to higher engagement from followers (Bakshy, Messing and Adamic, 2015). However, this approach may exclude potential customers who are not interested in the specific niche. Lastly, collaborating with influencers who have a broader reach and a clear resonance with the brand can help increase brand awareness among new customer groups while ensuring that the message is relevant to the influencer's audience. RunTartan needs to develop an appropriate strategy that balances the benefits and risks based on its marketing goals, target audiences, and brand values.

Clickstream Analysis for HaggisBus

HaggisBus has provided us with a web traffic dataset, and our aim is to identify the performance of different campaigns, platforms, and blog content to help HaggisBus improve its profit margins or return on investment.

Campaign Performance

LinkedIn's advertisement campaign outperformed Facebook and Partner's campaigns with a conversion rate of 25.2% (Figure 1) and an average page depth of 4, which highlights LinkedIn's ability to design an attractive website that keeps visitors engaged. This finding suggests that HaggisBus should focus on LinkedIn advertisements to improve its profit margins.

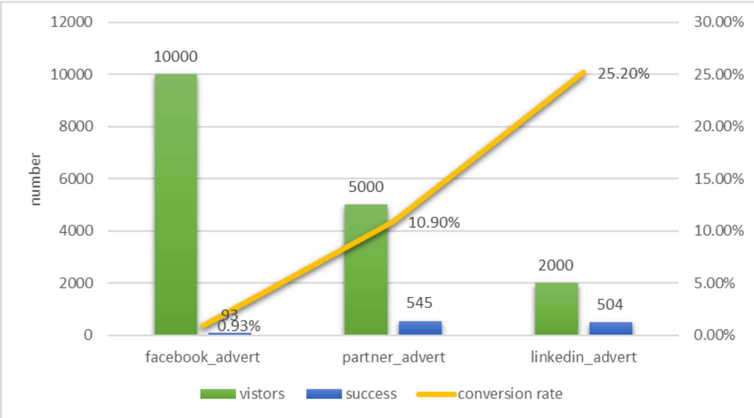

Figure 1: Performance of campaigns

Platform Behaviour

Figure 2 illustrates that the Windows platform has the highest conversion rate and longest visit duration compared to other platforms, while desktop platforms (Windows, Mac) have higher conversion rates than mobile ones (Android, iOS). The "contact_us" page has the highest exit rate, indicating that visitors may face technical issues or confusion about the buying process. Additionally, about 46.34% of visitors clicked on the "purchase_enter_address" page but did not complete their payments, indicating the need for a more user-friendly payment interface.

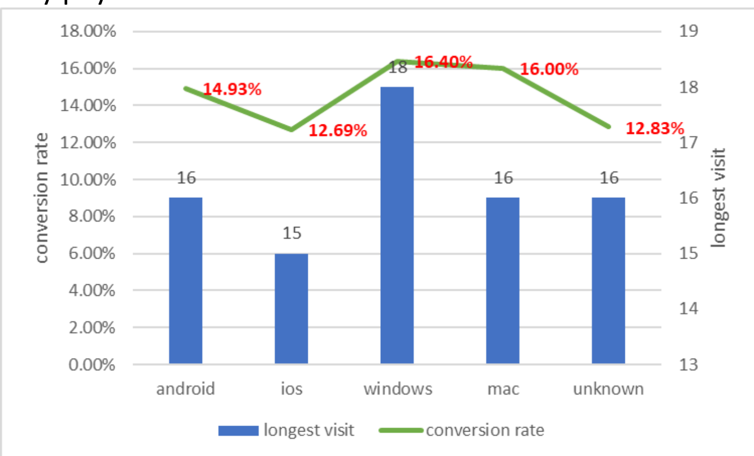

Figure 2: Performance of platforms

Origin Comparison

Social media shares induce more visitors to purchase HaggisBus's touring services (12.69%) compared to an advertisement. Visitors who typed HaggisBus's website URL are more likely to make payments (31.67%) than those who came via search engines (15.19%). This finding indicates that visitors who come directly to the site may have more interest in HaggisBus's services.

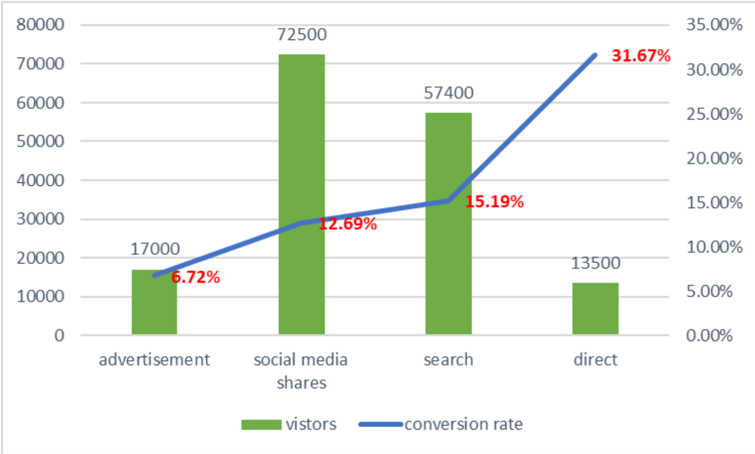

Figure 3: Performance of origins

Blog Performance

The conversion of a particular blog would be defined as the visitors going to the payment page after reading the blog, and if the user visited both blogs, the credit would be given to the blog just before the payment page ("purchase_success"). In Figure 4, blog_2 is seen to be more effective in converting readers to payment success, even though its absolute number of payment successes is not the highest. This suggests that HaggisBus should create similar content to blog_2 and use similar expressions to attract more visitors to their site.

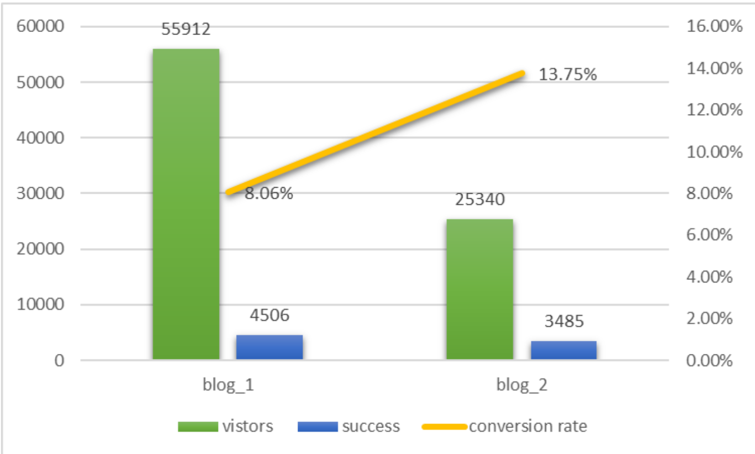

Figure 4: Performance of blogs

Conclusion

Based on our analysis, we recommend that HaggisBus focuses on the LinkedIn advertisement, the Windows platform, social media shares, and creating similar content to blog_2 to improve their profit margins and attract more visitors to their website. Additionally, HaggisBus needs to develop a more user-friendly interface to address technical issues or confusion about the buying process.

<u>Glossary</u>

Exit rate: The number of sessions where the session stops divided by the total number of visits, including that page.

Average page depth: The total number of pages divided by the total number of visits.

Conversion rate: The purchase confirmed rate.

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