Analysis Write Up - Apprentice Chef, Inc.

Insight #1

Users that signed up for their accounts using their professional work emails had shown strong significance in model performance. Users with professional emails totaled 36% (696 users) of the entire customer base and converted 80% of the time to the cross-sell campaign. With this information, we can potentially determine that users signing up with their work email could be earning more income, have less time to cook and prepare their food, and are at minimum age to consume wine. These users would be getting a more efficient cooking experience using Apprentice Chef's product and would purchase wine more frequently.

Insight #2

Classifying customers into discount levels, Basic, Premium, and no discount, there were no users in the basic discount, compared to 72% (1400) of users with a premium discount, and 546 users with no discounts. Surprisingly the wine promotion had the same success rate, 68% for both premium and no discount groups. One would expect that customers with discounts would be more attracted to the wine promotion. However, the company could be losing more money, offering a premium discount to customers who are not converting the cross-sell wine promotion. Financially the discounts could be counterproductive for cross-sell success.

Recommendation

The business opportunity for Apprentice Chef would be to increase its presence in corporate partnerships. We saw users with professional emails, produce more robust results in converting the wine promotion.

The startup culture, in particular, have great meal benefits, providing their employee's food at lunch and sometimes at night post work. On average, Apprentice Chef's meals cost $16.50, and a company spends $15-17 per employee meal (HighFive, 2019). Apprentice Chef should be approaching companies to provide exclusive partnership prices to supply their meals to their employees, so instead of staying back to eat lunch or dinner, they can head home and cook for themselves and their family.

Competitor Blue Apron, provide exclusive discounts for corporates depending on meal frequency and company size (Blue Apron). With these employees spending more time at home and enjoying the services from Apprentice Chef, the wine promotion could be easier to convert. Given that their employers will supply the employees Apprentice Chef meals, the employee could add the wine promotion out of their pocket and wouldn't incur that much cost overall.

Working with companies to supply meals to their employees could monumentally increase new users, grow revenue, and cross-sell success of the wine promotion.

Model Performance

- **Support Vector Machine (SVM) Model AUC Score: 0.818**

Sources

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