Hi Selorm,

Great use of the e-commerce email A/B test. Picture splitting 1,000 users into two equal groups of 500: if 30 users in the email group convert (a 6% conversion rate) compared with 24 users converting (a 4.8% rate) in the no-email group, that demonstrates a 1.2-percentage-point lift thanks to the emails (Campaign Monitor, n.d.).

I am curious about your matching and machine learning ideas for the billboard scenario. With 10 potential billboard sites and 10 control locations averaging 20,000 vehicles per day and $50,000 neighborhood income, which variables would you prioritize for matching? For a machine learning model, would you choose logistic regression first or jump to a random forest to catch nonlinear patterns (Austin, 2011)?

Your CATE insight reminded me that an overall 4% ad lift could mask subgroup effects, for example, a jump from 15% to 25% conversion among drivers under 30 (a 10-point gain), while drivers over 50 see a drop from 10% to 9% (a 1-point loss). This makes me rethink how I segment my fraud-risk analyses (CausalWizard, n.d.).

Thanks for sharing these practical scenarios. Could you give a quick example of matching 20 billboard-control pairs, maybe with sample reach numbers, and suggest the key question you would explore next?

All the best,

Avi

References

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