Unwrapping Customer Delight

Using Machine Learning to Optimize Surprise Gift Strategies

Estée Lauder

Problem Statement

Objective

To assess the impact of surprise gift campaigns on customer spending, determining if such gifts lead to increased engagement and spending.

Importance

Surprise gift campaigns are popular in customer engagement strategies but require quantifiable ROI to justify their value.

Solution

Develop a Bayesian Regression Discontinuity Design (RDD) to evaluate the effect of receiving a surprise gift on future spending.

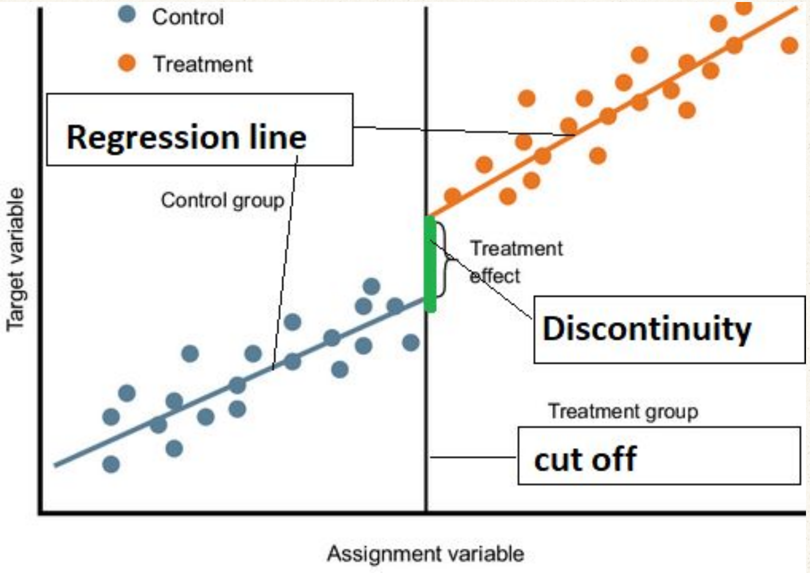
Important Terms

- Regression Discontinuity Design (RDD)
  - A way to compare customers just above and below a cutoff point to see if the gift made a difference
- Frequentist Analysis
  - A way to analyze data looking at patterns in data without relying on previous knowledge
- Bayesian Analysis
  - A method of analysis that combines new data with existing knowledge to update predictions
  - Models used: Uniform, Normal, Half Cauchy
- OLS (Ordinary Least-Squares)
  - A way to find the best straight line to describe the relationship between two things, here it's spending and receiving a gift

Research Question

Does receiving a surprise gift have a causal effect on customer spending, and if so, what is the measurable magnitude of this effect?

Regression Discontinuity Design (RDD)



Example of Regression Discontinuity Design. Source: Muhammad Asad Kamran, *Regression Discontinuity in Causal Inference: An Introduction*, February 26, 2023. Retrieved from LinkedIn.

RDD estimates causal effects by comparing observations just above and below a predetermined cutoff on a continuous assignment variable. The treatment's impact is isolated by analyzing the abrupt change in the outcome at the cutoff, with the regression line representing the relationship on either side.

Our threshold is determined via a bandwidth selection.

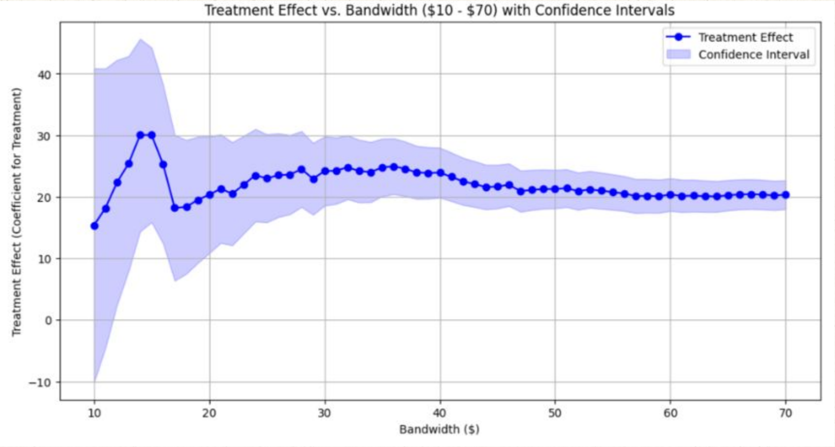
Bandwidth Selection: $55

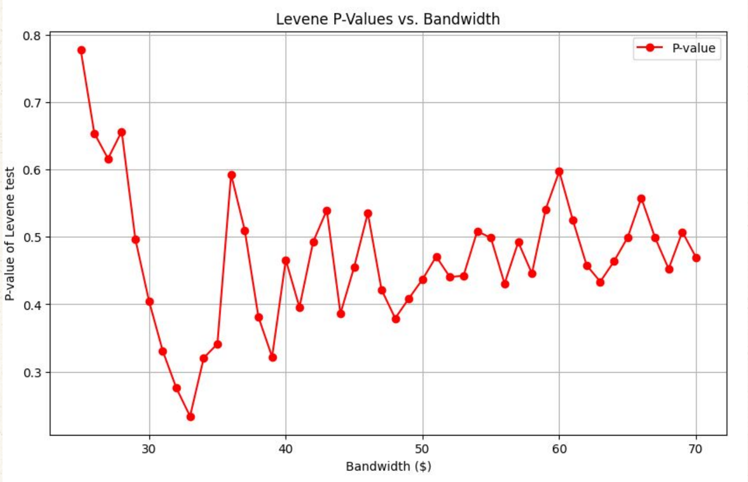
In a Regression Discontinuity Design (RDD), bandwidth selection is crucial because it defines the subset of data points near the treatment threshold used in the analysis.

Using our bandwidth of $55, we filtered our data set, from 20,000 data points to **16,451**, a retention rate of 82.25%. These points were used for further analysis with three models to analyze the treatment effect.

The bandwidth of $55 helps show how the treatment affects customers who spend within this threshold, making it more efficient to create optimal surprise gift strategies.

Bandwidth Selection cont.

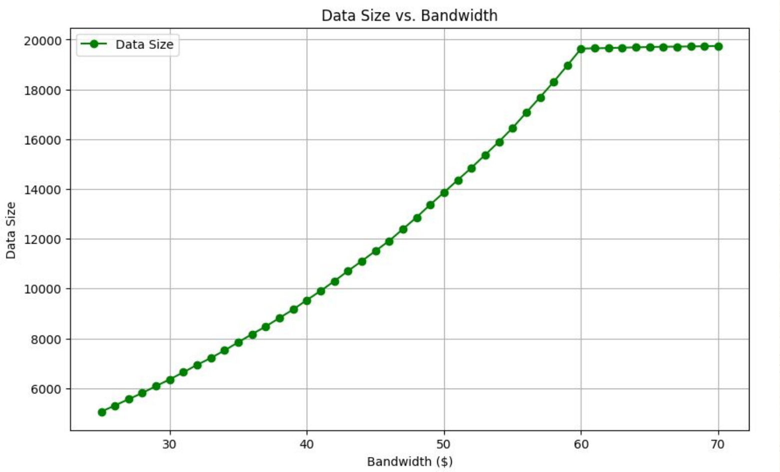




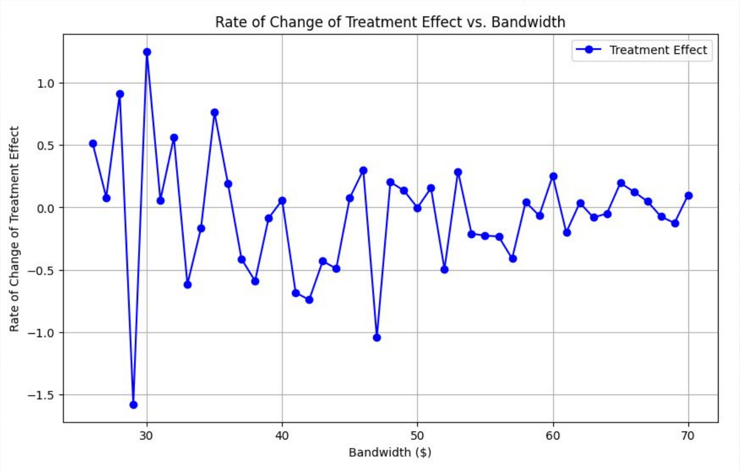
The optimal bandwidth of $55 is chosen to minimize bias while maintaining stable treatment effect estimates and tight confidence intervals, ensuring reliable causal inference.

Before $55, the p-values exhibit fluctuations, indicating an inconsistency between the treatment and control groups. Between $25 and $45, the p-values begin to stabilize but still show variability. This supports selecting $55 as the optimal bandwidth.

Bandwidth Selection cont.



The plot shows a clear upward trend, indicating that as the bandwidth increases, the data size increases. At bandwidth $55, the data size is large enough to ensure that outliers or noise do not overly influence the treatment effect estimates.



At a bandwidth of $55, the rate of change in the treatment effect stabilizes near zero, indicating that the treatment effect no longer fluctuates significantly as the bandwidth increases.

Two Methods of Inferencing

Frequentist

- Relies on long-run frequency and sampling, using observed data without prior assumptions to provide point estimates and confidence intervals.
- Frequentist method interprets probability as the frequency of an event in repeated trials.
- Frequentist analysis provides quick insights into the treatment effect, helping to set a benchmark.

Bayesian

- Uses prior beliefs and updates them with data to produce a posterior distribution, giving a range of probable values for parameters.
- Bayesian treats probability as a degree of belief, and thus incorporates prior knowledge.
- Bayesian analysis adds depth by accounting for uncertainty and incorporating prior knowledge, making it ideal for nuanced, real-world applications.

Frequentist Model

- Purpose
  - Ordinary Least Squares (OLS) regression to estimate the impact of 2021 expenditure and the treatment effect on 2022 expenditure.

- Linear Regression Model with Interaction Terms & Model Specification
  - $y_{2022} = \beta_0 + \beta_1 \cdot x_{2021} + \beta_T \cdot T + \boldsymbol{\beta_2} \cdot \mathbf{(x_{2021} \cdot T) + \epsilon}$

Key Points:

- Interaction Term : $\boldsymbol{\beta_2} \cdot \mathbf{(x_{2021} \cdot T)}$
  - Included to investigate whether the relationship between 2021 and 2022 expenditures changes depending on whether the customer received a gift.

Frequentist OLS Analysis

- Strong Model Fit
    - R-squared = 0.875: The model explains nearly 88% of the variation in 2022 spending.
- Positive Influence of Past Spending
    - Customers are expected to spend 110% of their 2021 spending in 2022, representing a 10% increase.
- Treatment Effect is Positive, but Diminishes with Higher Past Spending
    - Receiving the treatment is associated with a $20.77 increase in 2022 spending
    - However, this effect decreases as prior spending increases seen by the Interaction Term (-0.1993).
- Statistically Significant Results ($p < 0.001$)

OLS Regression Results

Dep. Variable:	Dollars Spent 2022	R-squared:	0.875
Model:	OLS	Adj. R-squared:	0.875
Method:	Least Squares	F-statistic:	3.833e+04
Date:	Tue, 19 Nov 2024	Prob (F-statistic):	0.00
Time:	05:32:03	Log-Likelihood:	-61122.
No. Observations:	16451	AIC:	1.223e+05
Df Residuals:	16447	BIC:	1.223e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	10.0695	0.267	37.708	0.000	9.546	10.593
Dollars Spent 2021	1.0975	0.006	192.891	0.000	1.086	1.109
Treatment	20.7680	1.476	14.070	0.000	17.875	23.661
Interaction	-0.1993	0.016	-12.837	0.000	-0.230	-0.169

Omnibus:	1.132	Durbin-Watson:	2.007
Prob(Omnibus):	0.568	Jarque-Bera (JB):	1.144
Skew:	0.000	Prob(JB):	0.564
Kurtosis:	2.959	Cond. No.	1.21e+03

OLS results for Frequentist Model fitted with $55 bandwidth

Bayesian Model

Purpose

Predicts 2022 spending based on:

- 2021 spending (x2021)
- Treatment effect (treatment)
- Interaction between them

Inference

Performed via NUTS (N-U-Turn-Sampler) using Uniform, **Normal** and **Half-Cauchy** distributions

Model Structure

Priors
Mean equation:
$\mu = \alpha + \beta_1 x_1 + \beta_2 T + \beta_3 (x_1 * T)$

α : intercept (baseline spending)
β_1 : effect of prior spending (2021)
β_2 : treatment effect (gift)
β_3: interaction between prior spending and receiving gifts

Assumptions

Causal framework using RDD
Independence of Observations
Reasonable and unbiased priors (e.g., Uniform, Normal, Half-Cauchy)

This model allows us to infer the effect of treatment on spending changes from 2021 to 2022 by **comparing posterior means**, especially **focusing on** β_2 **for treatment impact.**

Bayesian Analysis

Bandwidth Application

Using our bandwidth of $55, we filtered our data set, from 20,000 data points to **16,451**, a retention rate of 82.25%. These points were used for further analysis with three models to analyze the treatment effect.

Uniform

- Mean treatment effect of $20.75
- Posterior distributions were relatively stable.

Normal

- Mean treatment effect of $19.11, which agrees fairly well with OLS
- Posterior distributions confirmed convergence.

Half-Cauchy

- Mean treatment effect of $19.11
- Posterior distributions confirmed convergence.

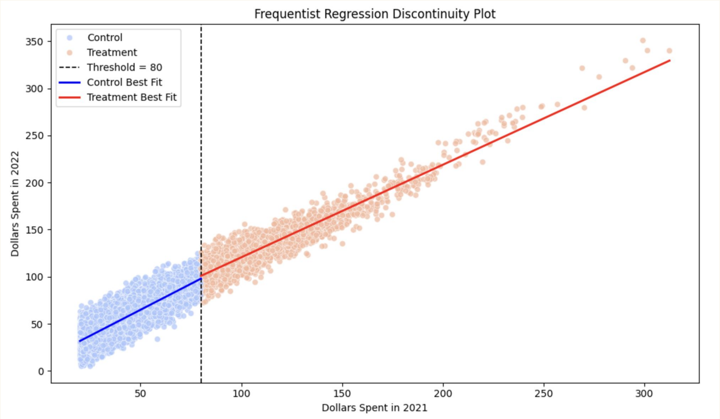
Conclusions

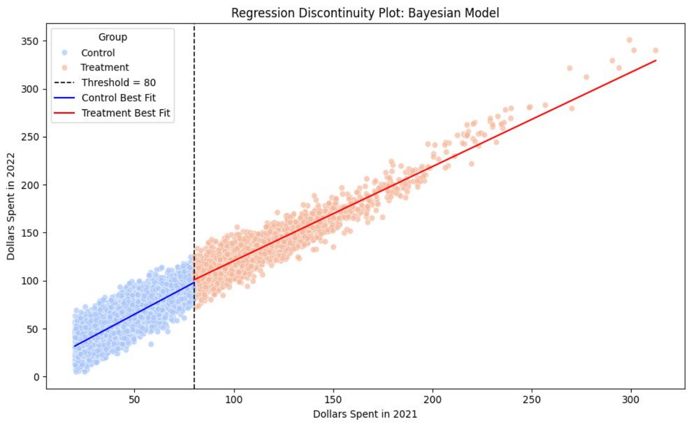
This Bayesian analysis shows a **significant positive impact** of receiving a gift on future spending with the treatment effect consistently across all models. This analysis provides evidence that the **gift treatment likely increases customer spending**.

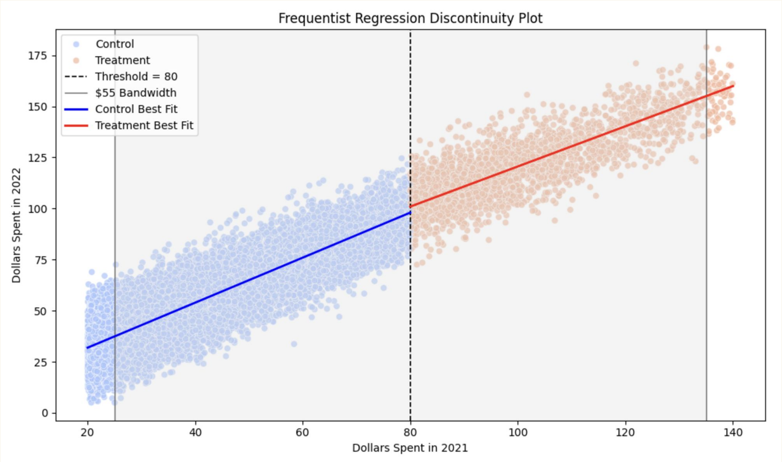
Comparison Between Models

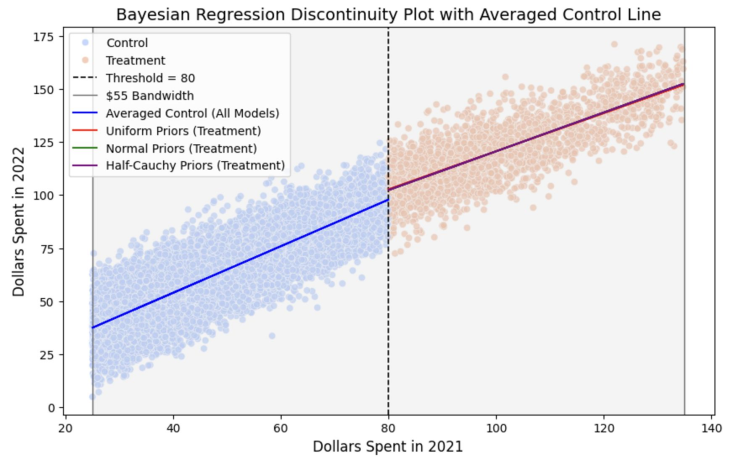
	Frequentist Model (OLS)	Bayesian Models
Goodness of Fit	**R-squared:** Explains 87.5% of variance; strong fit with minimal unexplained variance.	**Trace Plots:** Stable, confirming a good fit.
Handling of Uncertainty	**Treatment effect:** Provides fixed value with confidence intervals.	**Posterior distributions** reflect uncertainty in parameters. **Credible intervals:** (94% HDI) offer probabilistic insights into treatment effects. Incorporates **prior beliefs** (Normal, Half-Cauchy), enabling more realistic modeling.
Treatment Effect	**Estimate:** 20.7, potential overestimation due to unmodeled variability.	**Estimates:** Conservative, ranging from 20.7 (U20.7niform Priors) to 19.1 (Normal, Half-Cauchy Priors). Reflects cautious and realistic modeling through **uncertainty incorporation.**

Regression Discontinuity Design Plots









Findings

- Treatment Effect:
    - Frequentist → $20.77
    - Bayesian Model→ $19.11

- While the results are fairly similar, the Bayesian Model offers a more robust estimate, grounded in prior knowledge.

- If the surprise gift is valued at $10, the Bayesian Model predicts an **ROI of ~91%** when customers received a surprise gift in 2021 and spent $19 more in 2022.

Recommendation

- Given these findings, we recommend that The Estée Lauder Companies prioritize the Bayesian framework for evaluating and refining future surprise gift campaigns.

- The substantial ROI via a Bayesian framework on the simulated data highlights the economic viability of surprise gift campaigns.
  - ROI of 91% signifies that the revenue generated from the campaign nearly doubled from the investment cost.

- We thus recommend the continuation of surprise gift campaigns for customers within the spending bandwidth of $55.

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BREAK THROUGH TECH

References

01 [Bayesian Regression Using NumPyro]

02 [Example of RDD Design]

03 [Ordinary Least Squares]

04 [NumPyro Documentation]