Neural Insights for Digital Marketing Content Design

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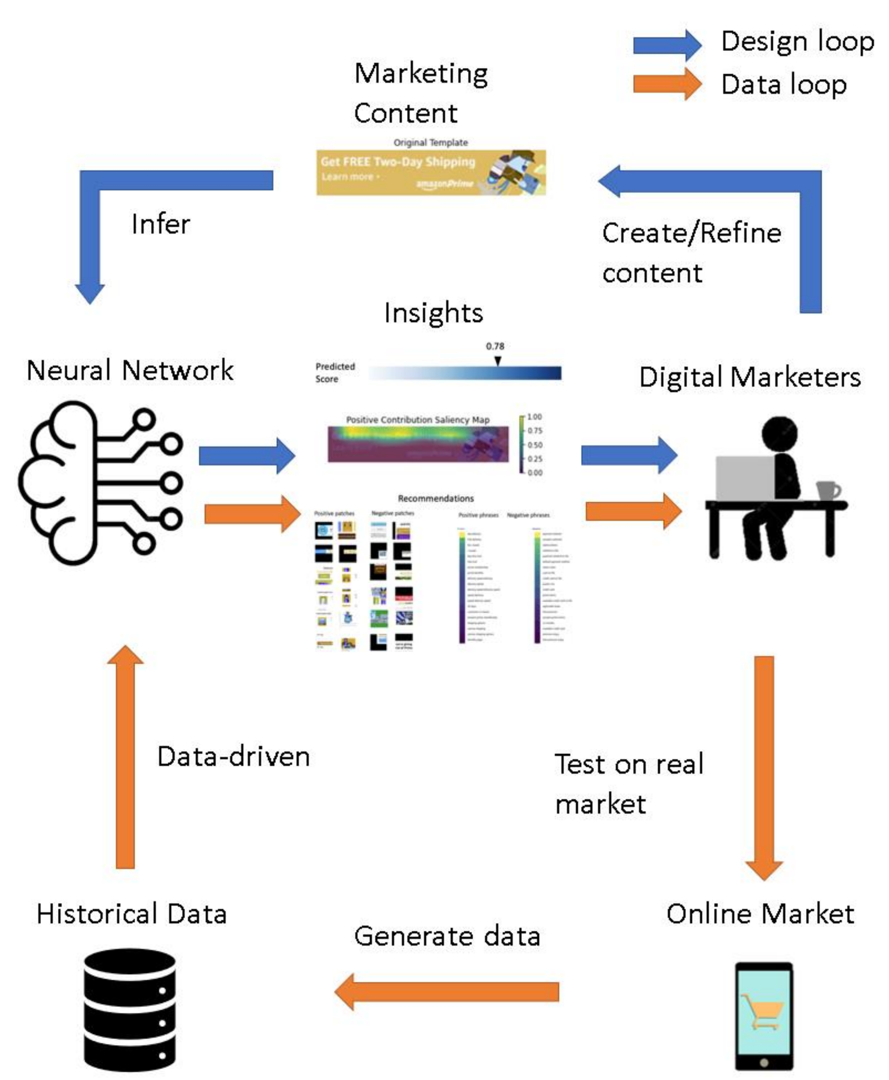
Motivation



Traditional content experimentation loop is:

- **labor-intensive;**
- **heavily dependent on expert knowledge;**
- **challenging to scale up with big data.**

Hence, our work seeks to close the loop between content creation and online experimentation by offering marketers AI -driven insights that are:

- **data-driven;**
- **versatile;**
- **actionable and real-time.**

Problem Formulation

Target Prediction: $Y = N_{clicks}/N_{total}$

Neural network modeling:

$$I_{emb} = \mathrm{ResNet}(I), \quad T_{emb} = \mathrm{BERT}(T),$$
$$D_{emb} = \mathrm{MLP}_1(D), \quad F_{emb} = \mathrm{MLP}_2(F).$$
$$\hat{y} = C(X_{emb}) = \mathrm{MLP}_3(\{I_{emb}, T_{emb}, D_{emb}, F_{emb}\}).$$

Input data:

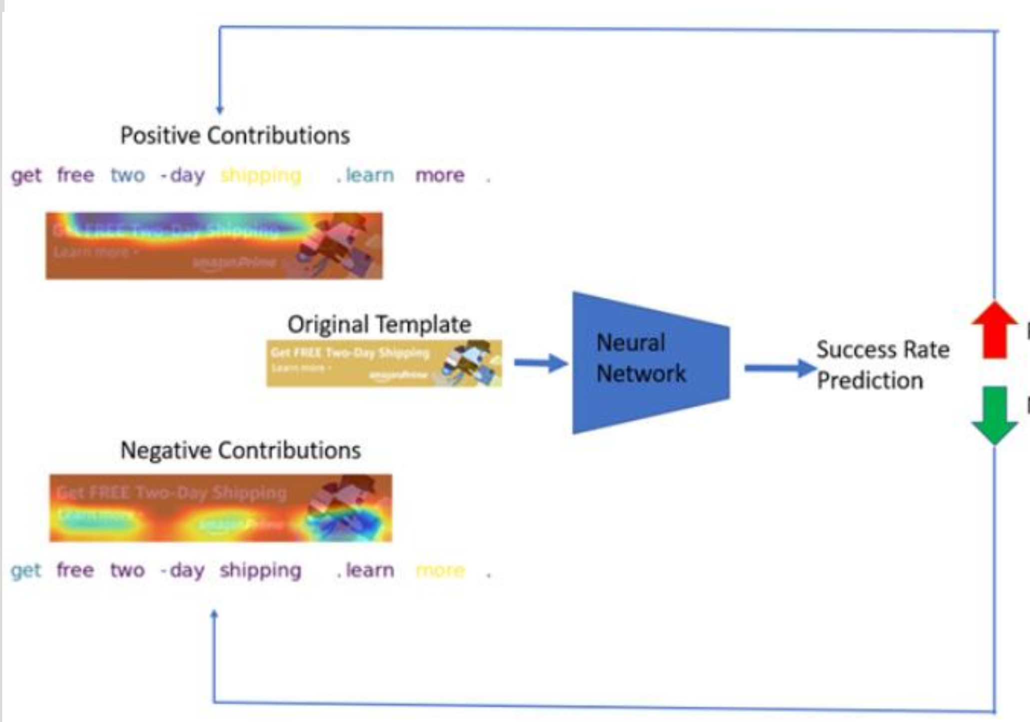
Content screenshot(Image): I

Promotion campaign(Text): T

Content domain: D

Handcrafted features: F

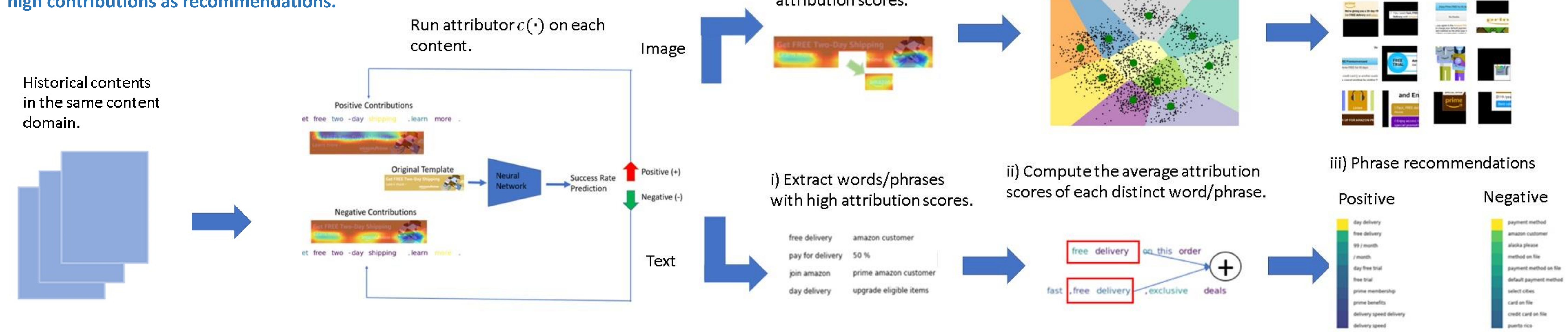
Goal: assume $Y = \sum_{x \in X} y(x)$ and $C(X) = \sum_{x \in X} c(x)$, we can get $\mathbb{P}[y(x) \neq c(x)] \to 0$



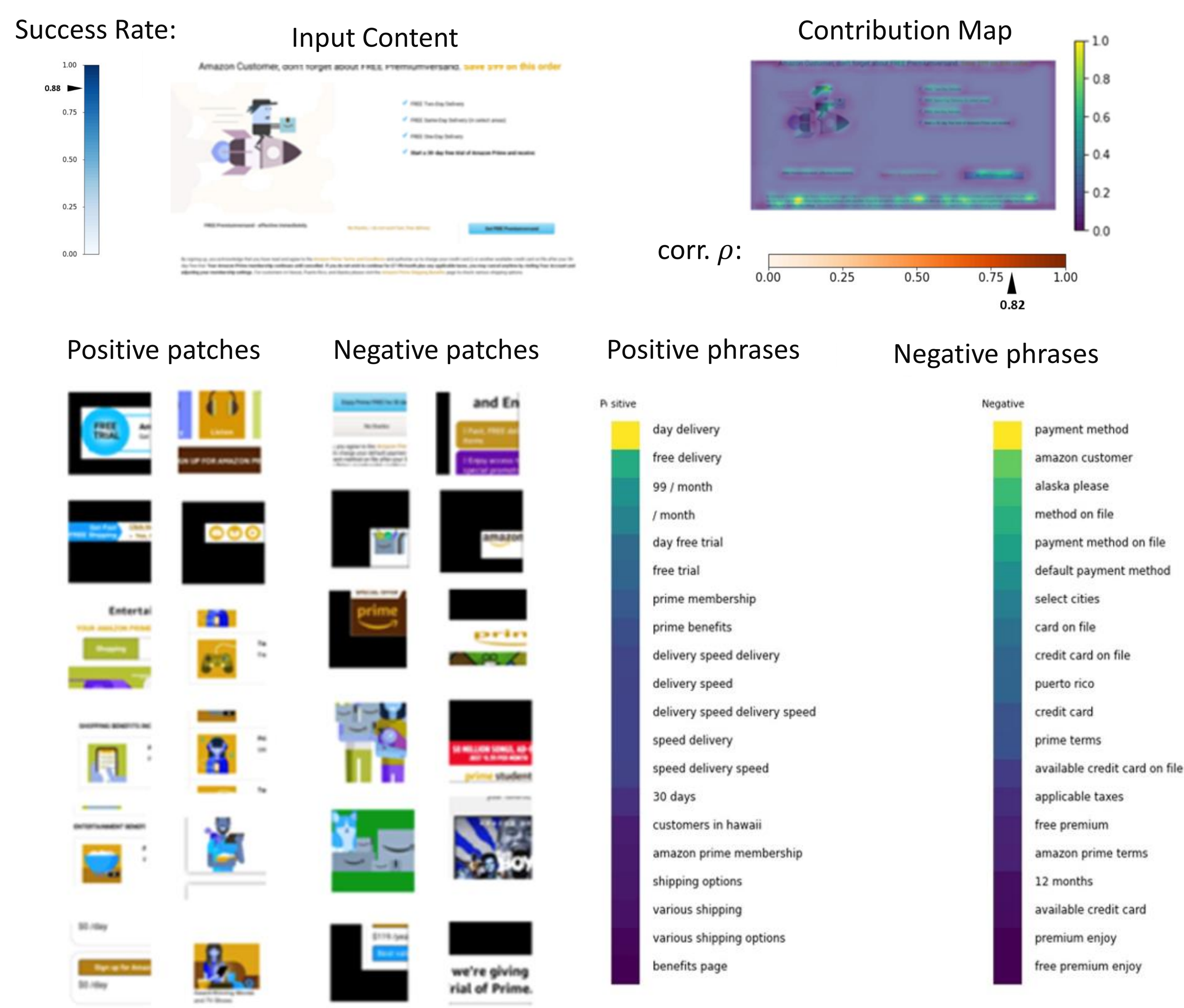
- **The goal is to understand how to improve the target prediction by modifying current input content.**
  - **We first train a multimodal neural network that can accurately predict success rate based on input contents.**
- **Then, we infer the fine-grained contributions of input and recommendations for improvement.**

Neural Insights and Recommendations

- **Neural insights leverages post-hoc attribution methods to interpret the output from multimodal neural network.**
- **Text recommendations summarize words and phrases with high average attribution scores.**
- **For image recommendations, we extract distinct design patterns by clustering with high contributions as recommendations.**



Visual Results



Insights Evaluation

Algorithm 1: A generic three-step approach to evaluate insights of attributor $c(\cdot)$.

Data: Input pairs of control bags and treatment bags (X, X'), $\forall X, X' \in \mathcal{X}$ and (Y, Y'), $\forall Y, Y' \in [0, 1]$ are the pairs of control labels and treatment labels respectively, and the evaluated attributor $c(\cdot) : \mathbb{R}^n \to [0, 1] \subset \mathbb{R}$.

Result: Correlation coefficient ρ.

Step *i***).** Compute the distinct elements set S, such that the attributes in S can be only found in X or X'.

$S := \{x | (x \in X \wedge x \notin X') \cup (x \notin X \wedge x \in X')\}$;

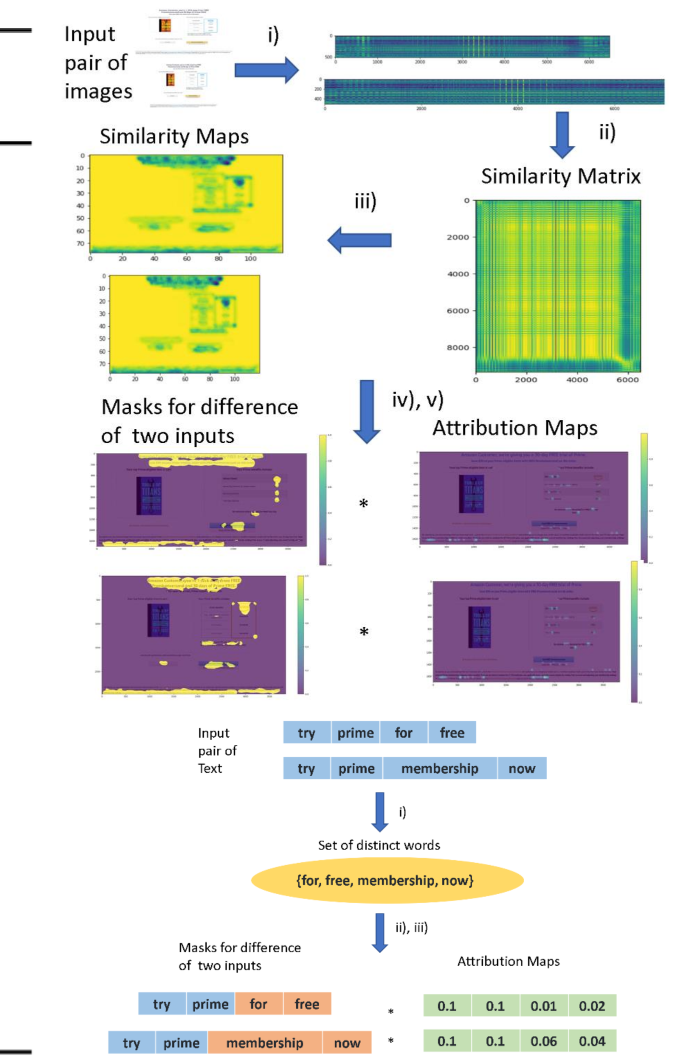
Step *ii***).** Compute predicted attribution difference d_C and actual success rate improvement d_Y:

$\mathbf{d}_C := \mathrm{sign}(Y' - Y)(\sum_{x \in (X' \cap S)} c(x) - \sum_{x \in (X \cap S)} c(x))$;

$\mathbf{d}_Y := |\Delta Y|$;

Step *iii***).** Examine the linear relationship of variable $\mathbf{d}_C$ and variable $\mathbf{d}_Y$ by computing the Pearson Correlation ρ on the whole dataset.

Output ρ.



$$\rho = \frac{\mathrm{cov}(\Delta c(x), \Delta Y)}{\sigma_{\Delta c(x)} \sigma_{\Delta Y}},$$

The metric aims to catch the relationship between insights-guided modifications ΔC and the ensuing change in the actual success rate ΔY.

Please check out the numerical results, detailed algorithms in our main paper!