Neural Insights for Digital Marketing Content Design

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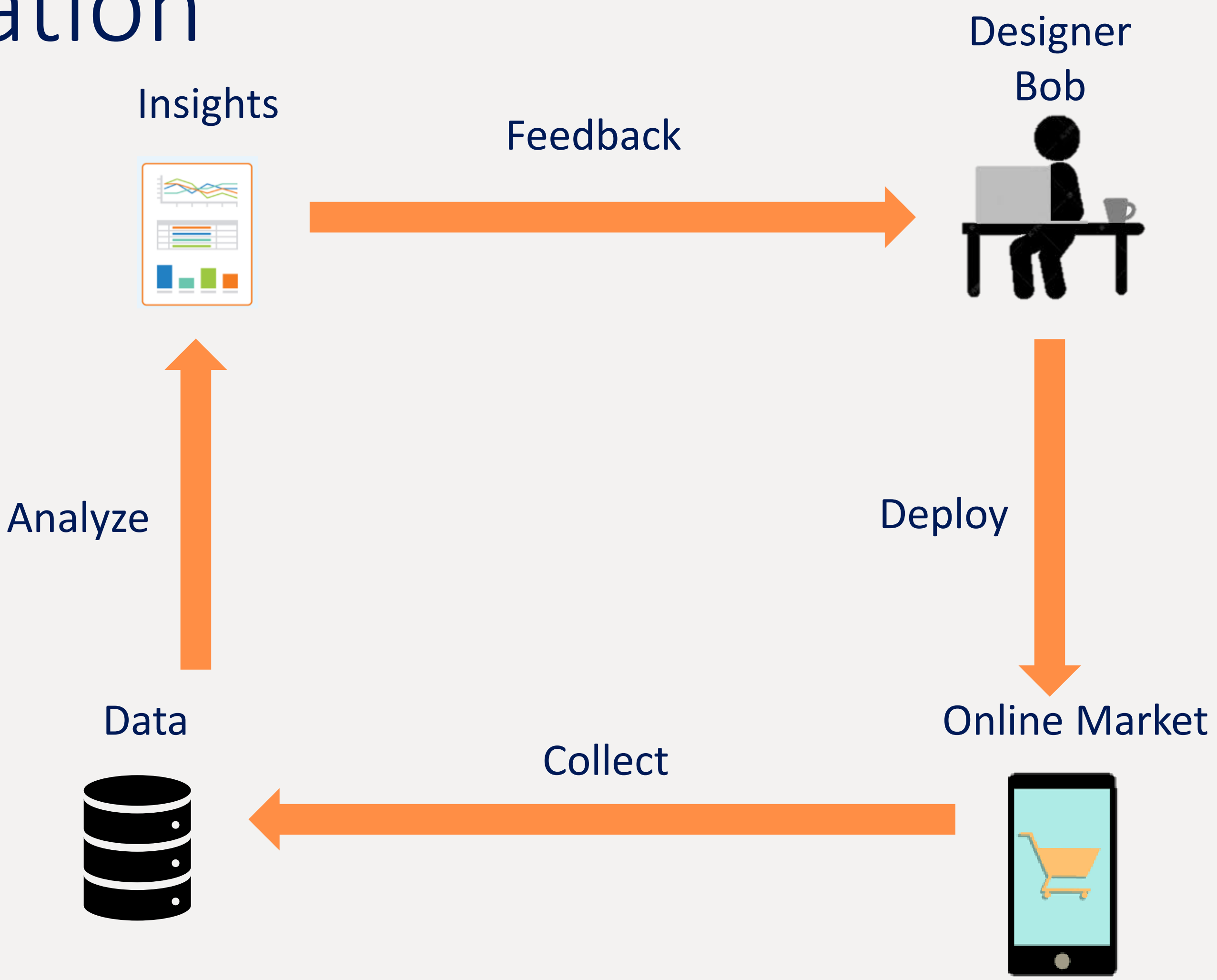
Introduction

Content Experimentation

Traditional content experimentation relies on A/B testing:

- Time-consuming
- Labor costs
- Lagging



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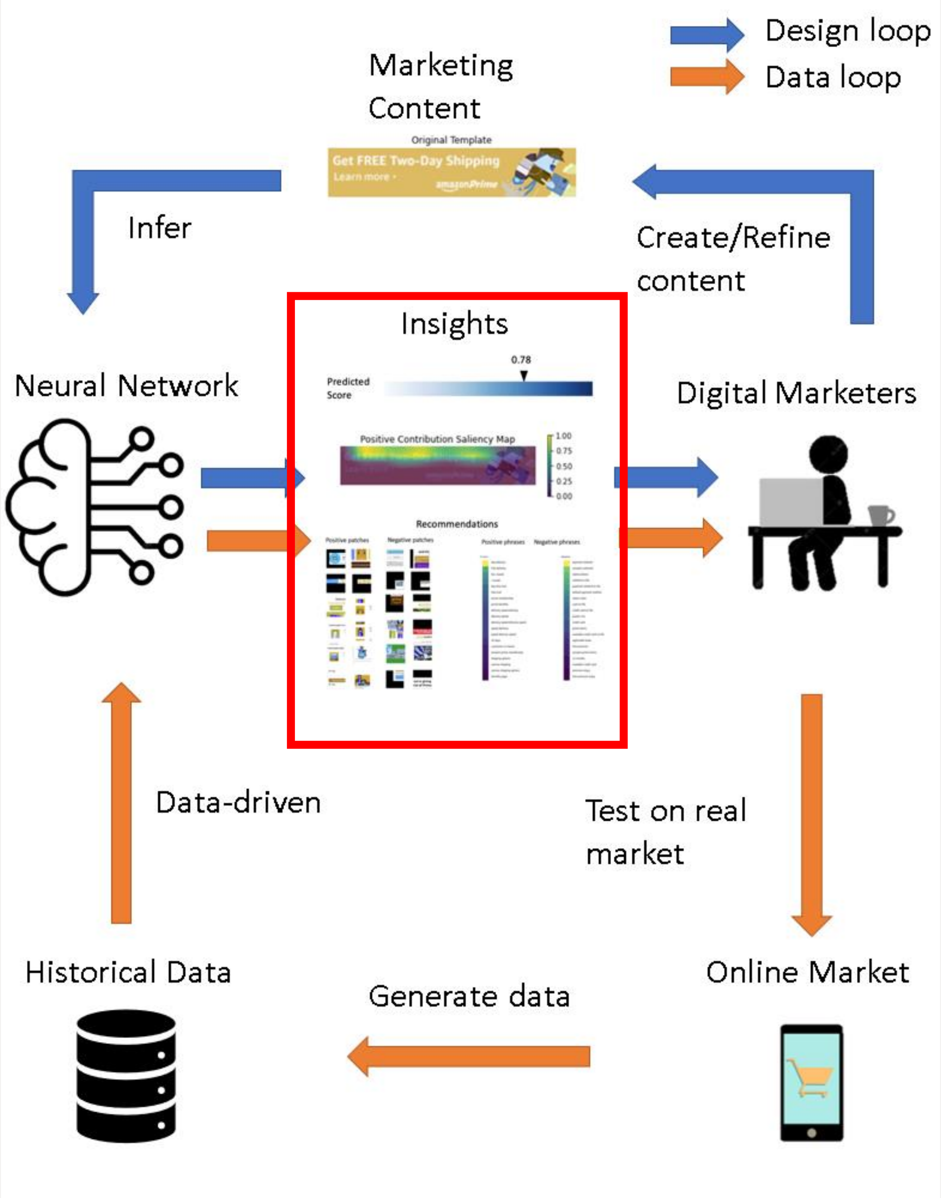
Research motivations

Hence, we introduce AI-driven insights into content experimentation loop:

- real-time
- versatile

- Triplet insights:
  - Input success rate
  - Element-wise contributions
  - Design recommendation



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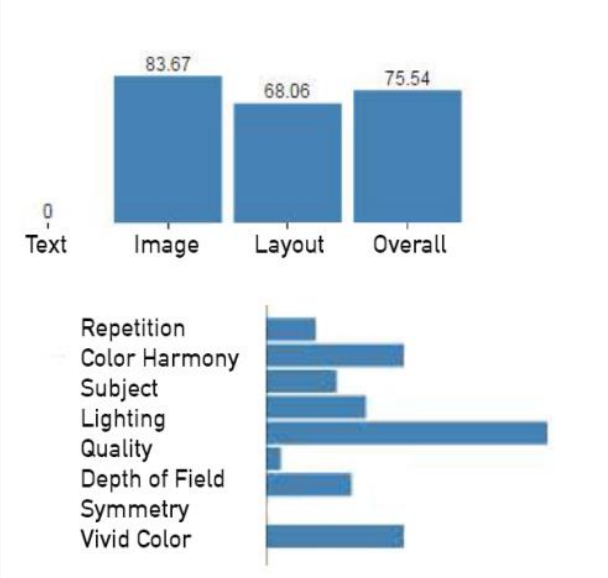
Related work

Previous digital marketing content insight framework:

- Sinha et al. leverages abstracted handcrafted features and linear regression.
  - Not actionable
  - Not scalable



[1] Sinha, Moumita, Jennifer Healey, and Tathagata Sengupta. "Designing with AI for digital marketing." *Adjunct Publication of the 28th ACM Conference on User Modeling, Adaptation and Personalization*. 2020.

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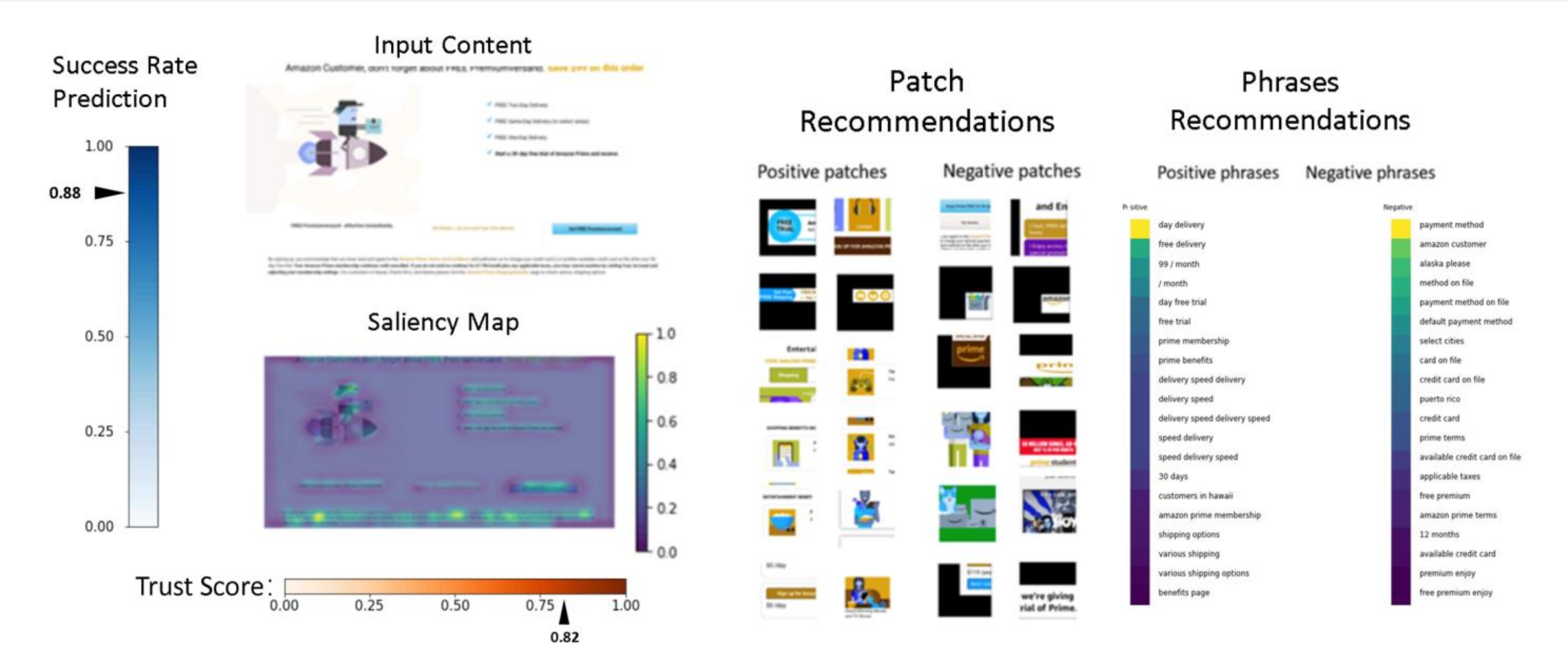
Our contribution

- 1. a novel image and text insight-generation framework
- 2. a novel insight evaluation framework
- 3. a demo system that generates interpretable insights in an interactive visual format



Methodology

Pipeline

- 1. Train a multimodal neural network with digital marketing data
- 2. Interpret output from the multimodal neural network and provide recommendations based on historical data
- 3. Evaluate the interpretations

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Marketing content modeling

- Input:

  Content screenshot(Image): I

  Promotion campaign(Text): T

  Content domain: D

  Categorical features: F

- Neural network modeling:

$$I_{\text{emb}} = \text{ResNet}(I), \quad T_{\text{emb}} = \text{BERT}(T),$$
$$D_{\text{emb}} = \text{MLP}_1(D), \quad F_{\text{emb}} = \text{MLP}_2(F).$$

$$\widehat{y} = C(X_{\text{emb}}) = \text{MLP}_3(\{I_{\text{emb}}, T_{\text{emb}}, D_{\text{emb}}, F_{\text{emb}}\}).$$

- Target prediction:

$$\mathrm{Y} = \mathrm{N}_{\text{clicks}}/\mathrm{N}_{\text{total}}$$

- Goal:

  assume $\boldsymbol{Y} = \sum_{x \in X} \boldsymbol{y}(\boldsymbol{x})$ and $\boldsymbol{C}(\boldsymbol{X}) = \sum_{x \in X} \boldsymbol{c}(\boldsymbol{x})$,

  we can get $\mathbb{P}[\mathbf{y}(\mathbf{x}) \neq \mathrm{c}(\boldsymbol{x})] \rightarrow \mathbf{0}$

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Pipeline

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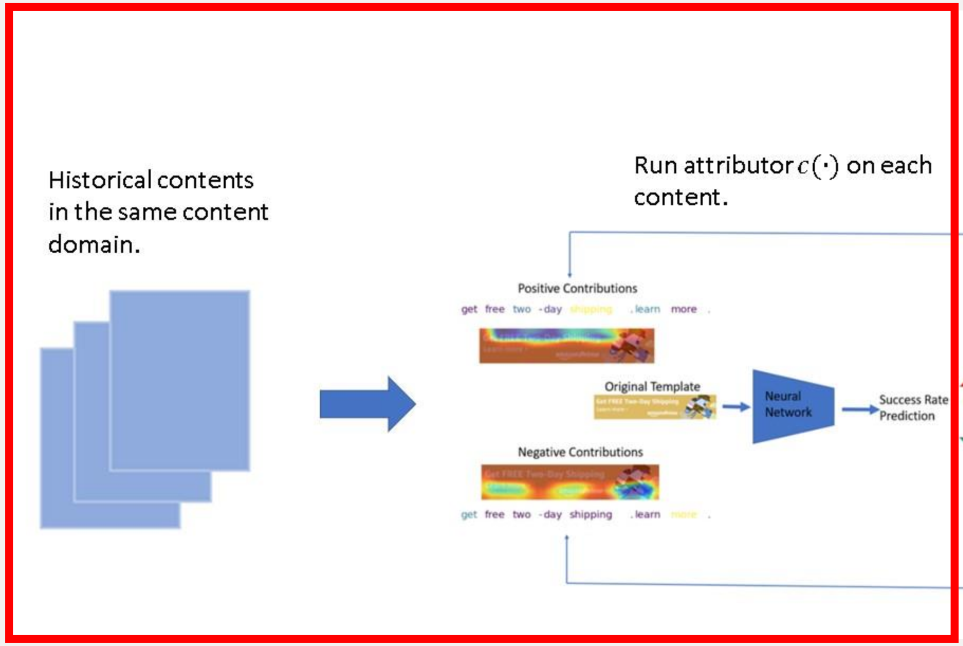
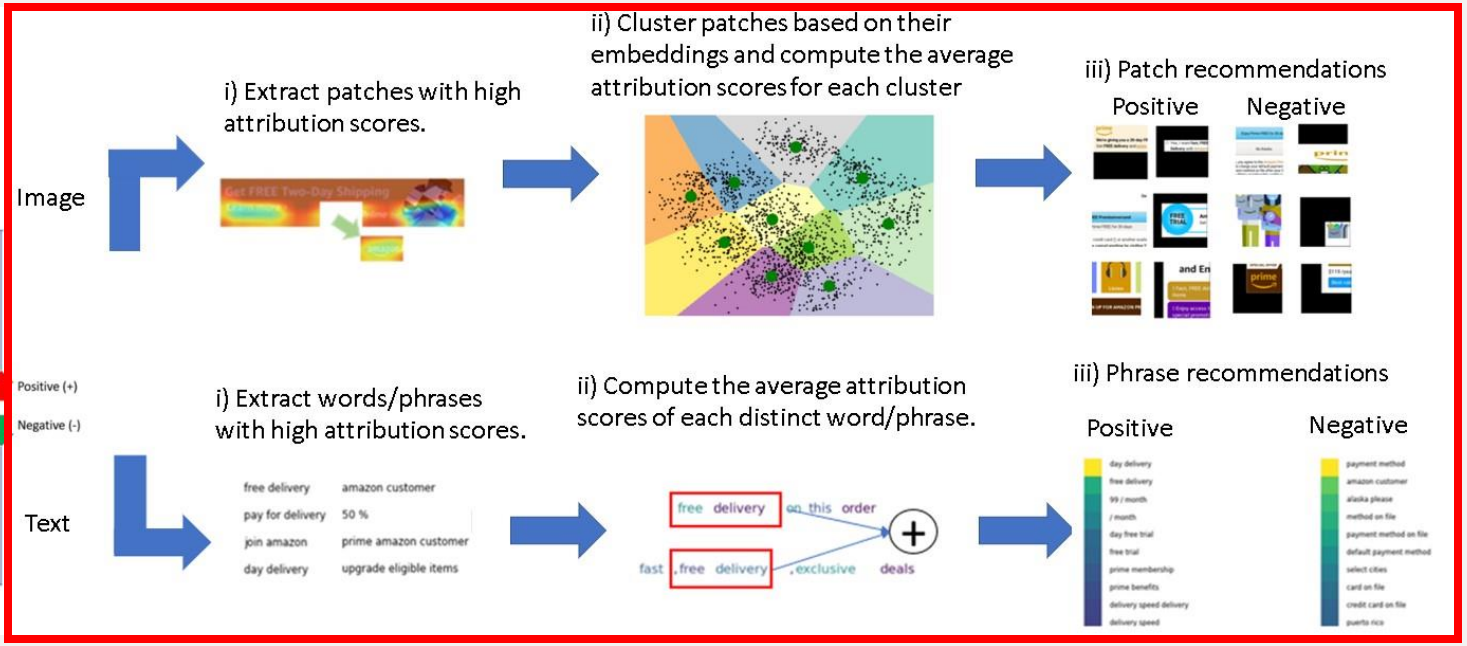
Neural insights generation

- 1. generate insights overlaid on marketing contents
- 2. summarize historical insights and provide image and text recommendations.





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Pipeline

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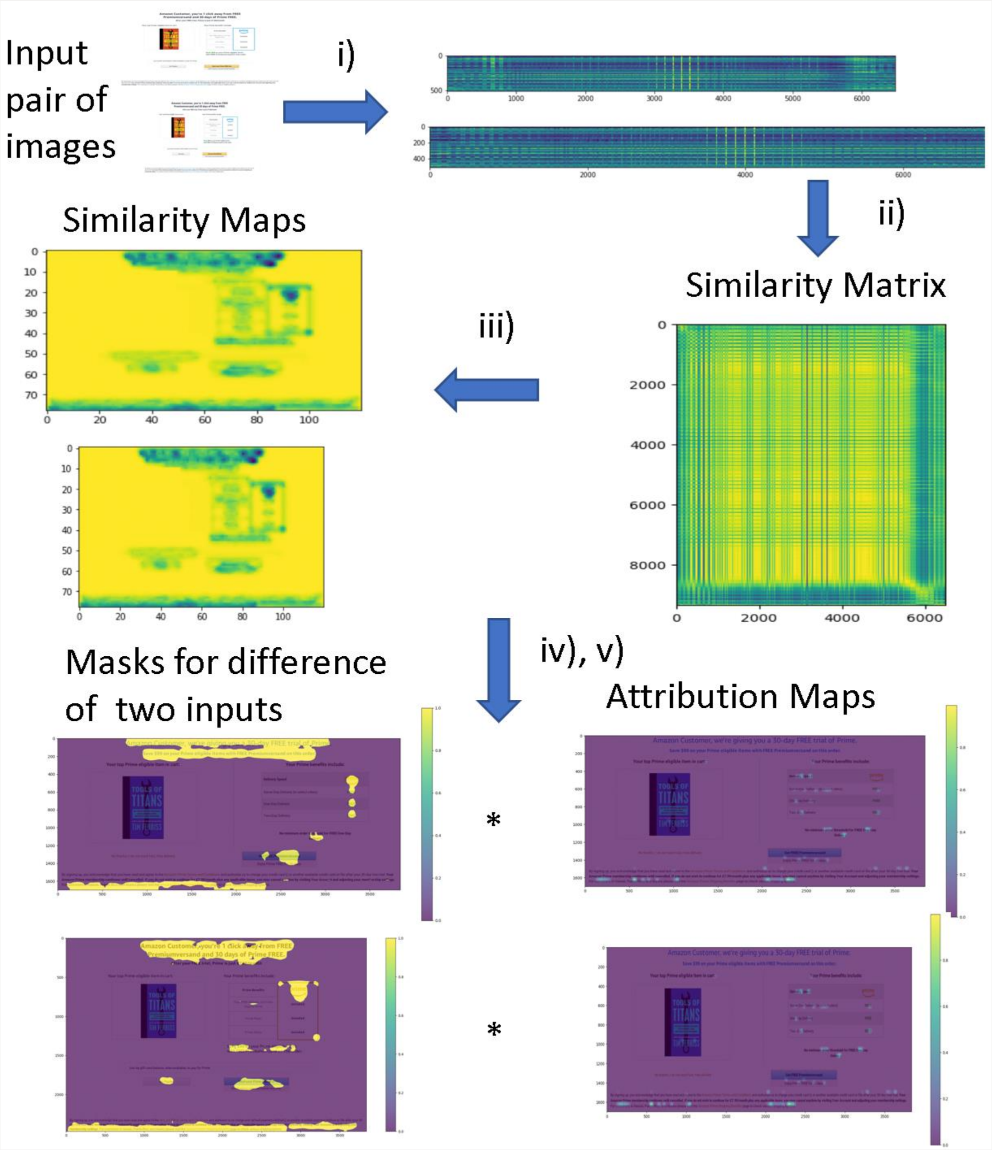
Evaluation Metric

- Existing evaluation metrics of interpretations are heuristic, spanning faithfulness, stability and fairness[1].

- Correlation between the difference of interpretation and the change of outcomes.

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

- Δc(x): difference of interpretation score for design elements in a content and their substitutes in another content .
- Δ Y: the actual change of outcomes.



[1] Agarwal, Chirag, et al. "Openxai: Towards a transparent evaluation of model explanations." *Advances in Neural Information Processing Systems* 35 (2022)

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Experiment

Experiment design

- Dataset: Amazon industry dataset
  - Each marketing content is equipped with an image screenshot, text campaign, categorical features and marketing domain.
  - Target: success rate
- Evaluation:
  - Success rate prediction accuracy
  - Insights evaluation
  - Visual examples of generated insights
  - Demo experiences from users

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Success rate prediction accuracy

Table 1: Success rate prediction results for different models and modality combinations. We show the percentage decrease of RMSE and MAE for each model compared to GLM.

Model	Modality	In-domain test set RMSE change ⬇	In-domain test set MAE change ⬇	Out-of-domain test set RMSE change ⬇	Out-of-domain test set MAE change ⬇
GLM	Categorical Features	0 %	0%	0%	0%
MLP	Categorical Features	-42%	-31%	-44%	-35%
MLP	Domain	-54%	-33%	-50%	-29%
XGBoost	Categorical Features	-38%	-9%	-41%	-24%
ResNet-18	images	-25%	19%	-38%	-12%
BERT	Text	-59%	-64%	-59%	-66%
Multi-modal Neural Network	All modalities	**-68%**	**-65%**	**-66%**	**-75%**

- Each modality is helping modeling the success rate.

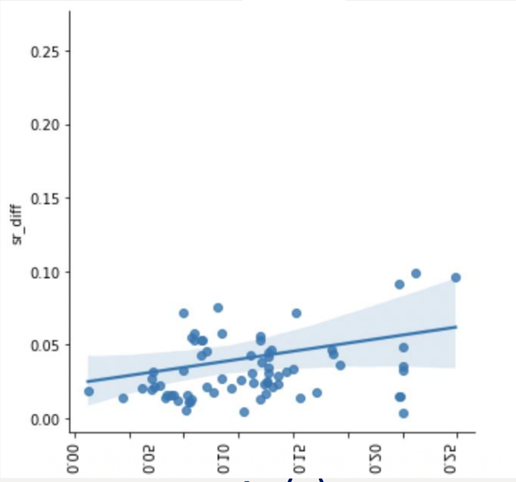
Insights evaluation

- How much the marketer can trust with the insights

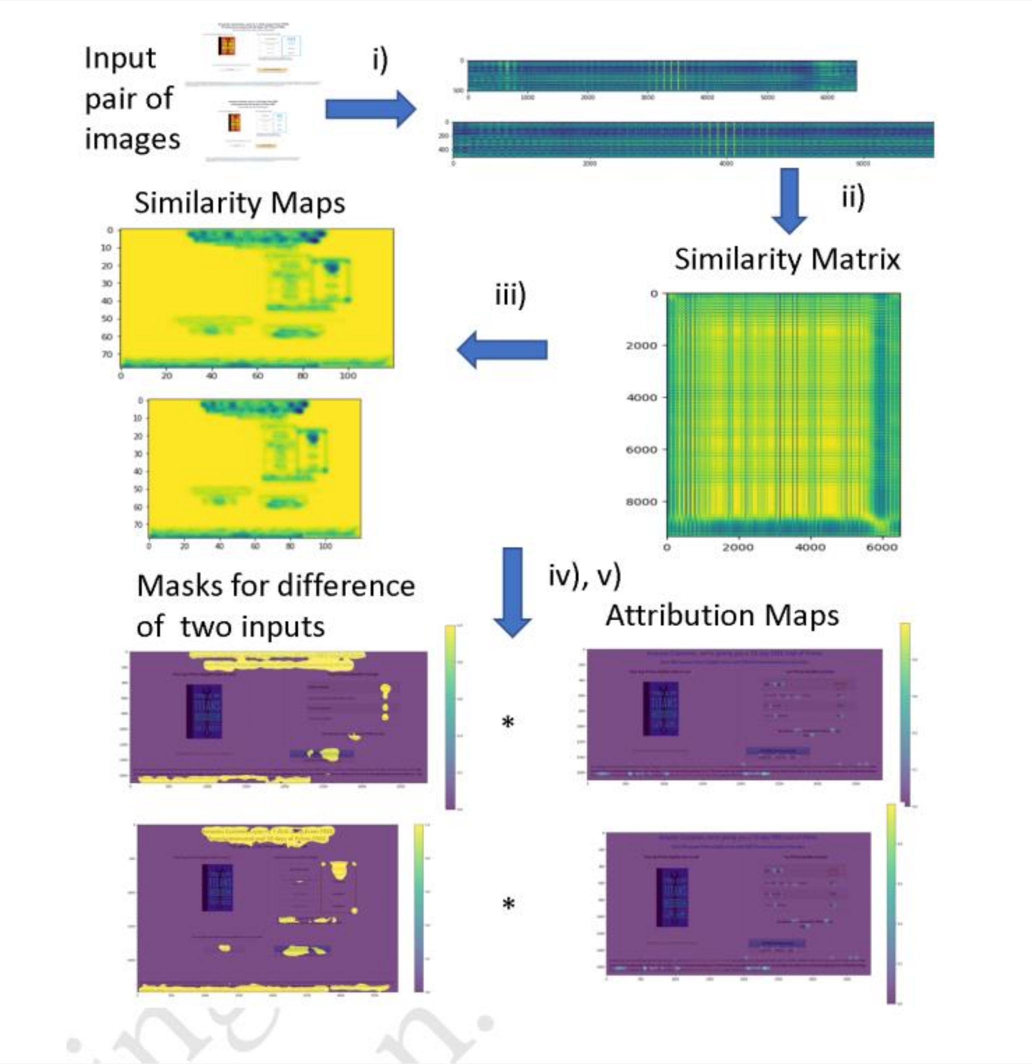
	GradCam	Integrated Gradient	Kernel SHAP	Feature Ablation	PCA
$\Delta\rho_{\text{text}}$ ↑	0%	+288%	+109%	-14%	**+493%**
$\Delta\rho_{\text{image}}$ ↑	0%	+55%	-18%	+0.5%	**+145%**

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

ΔY



Δc(x)



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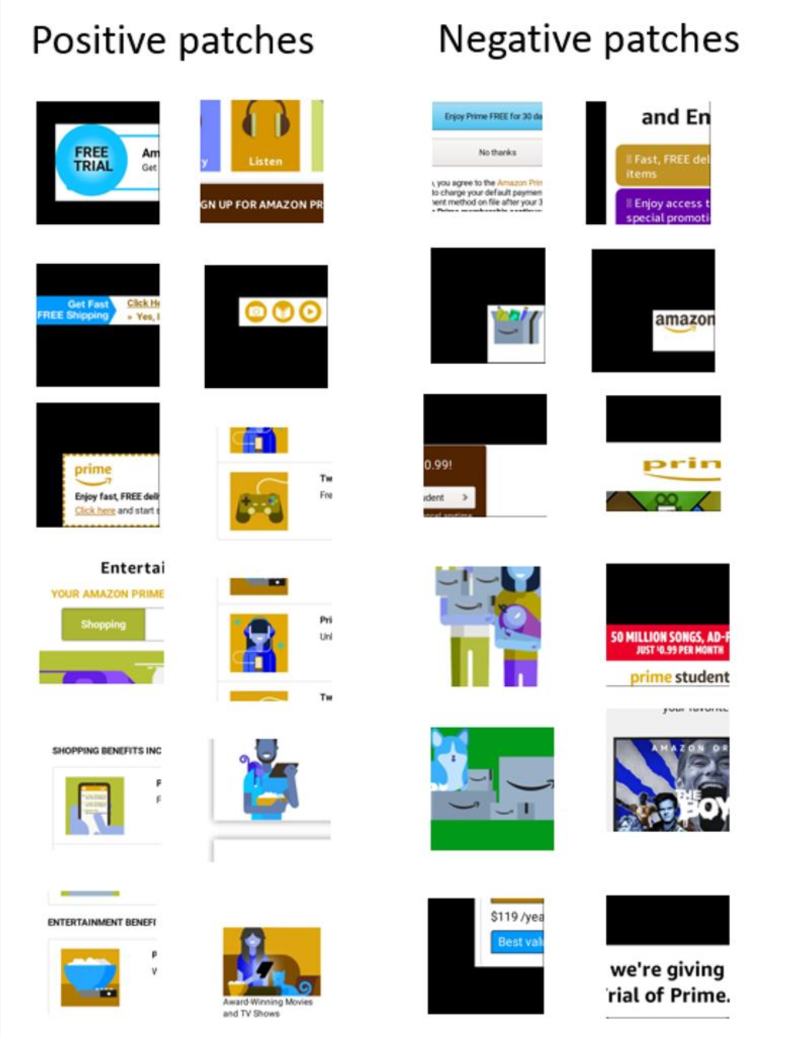
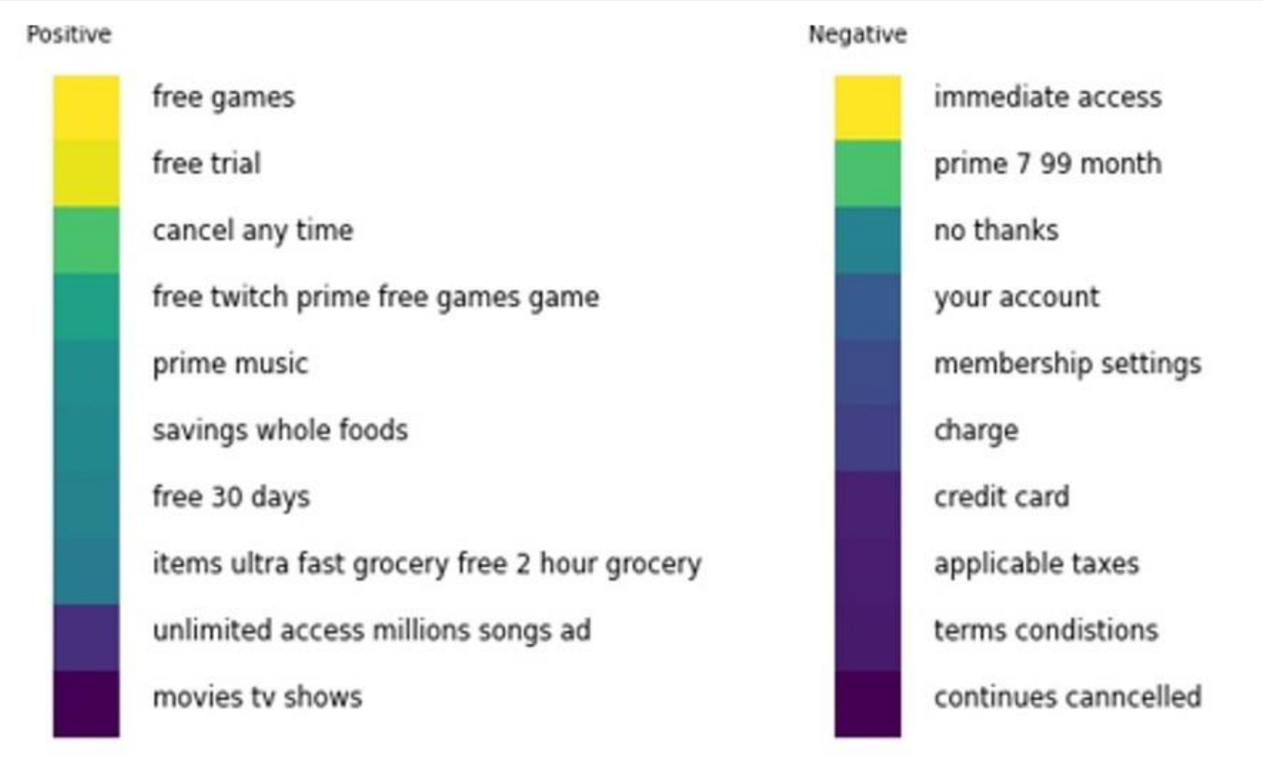
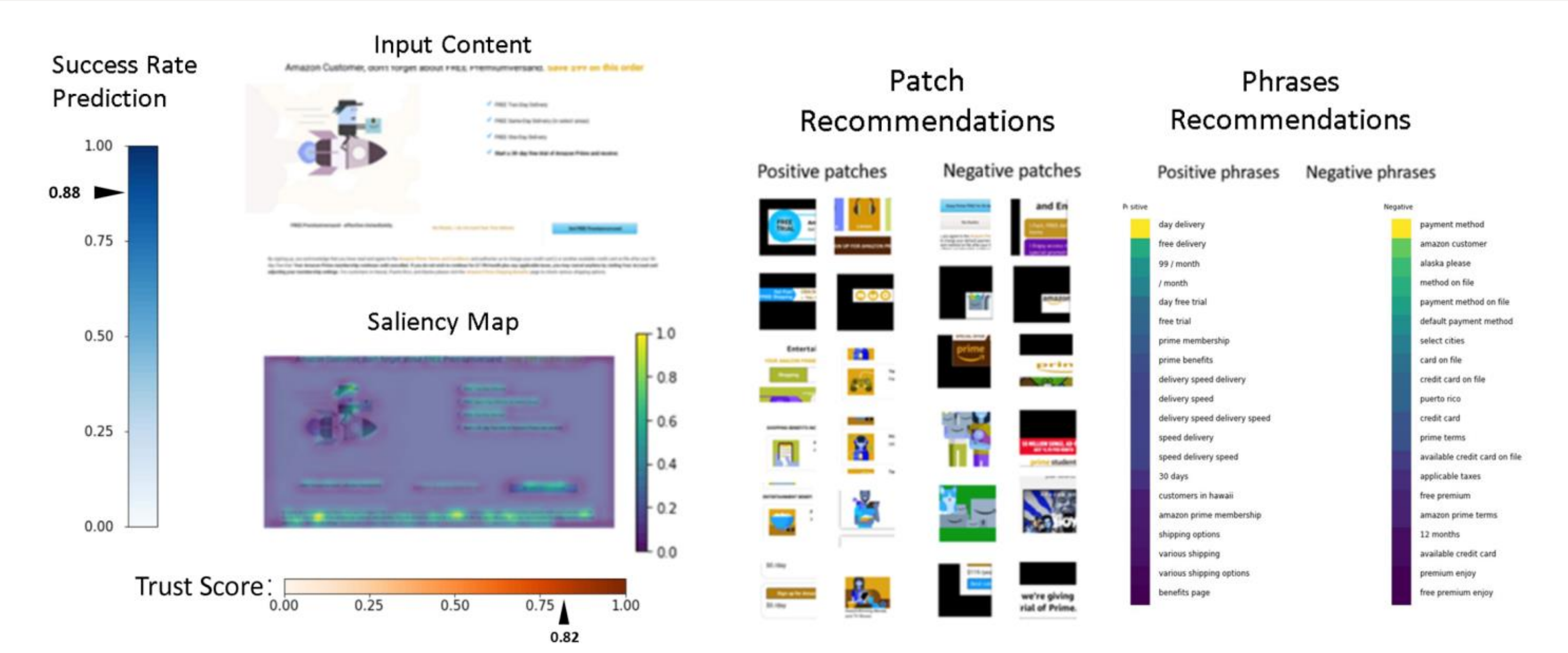
Visual examples of insight recommendation





Demo experiences from users

- We launched a demo among digital marketers in industry.
- Message from a marketer:
- “The new demo visualization insights helped make **analyzing our current templates faster** - allowing marketers to spend more time **identifying opportunities, create hypotheses, and test new experiences** based on the results. We are looking forward to continue working to develop this tool and use it to help with successful experiments!”



Future works

1. Explore causal-aware models for modeling content experimentation;
2. Integrate high-capacity language and vision models such as ChatGPT and SAM into our framework;
3. Extend the application of insight evaluation metric
   - For example, quantifying the estimated contributions of biological risk factors on healthcare costs or examining the effectiveness of a predicted business decision from an AI agent on the company’s income/loss.

Thank you.

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