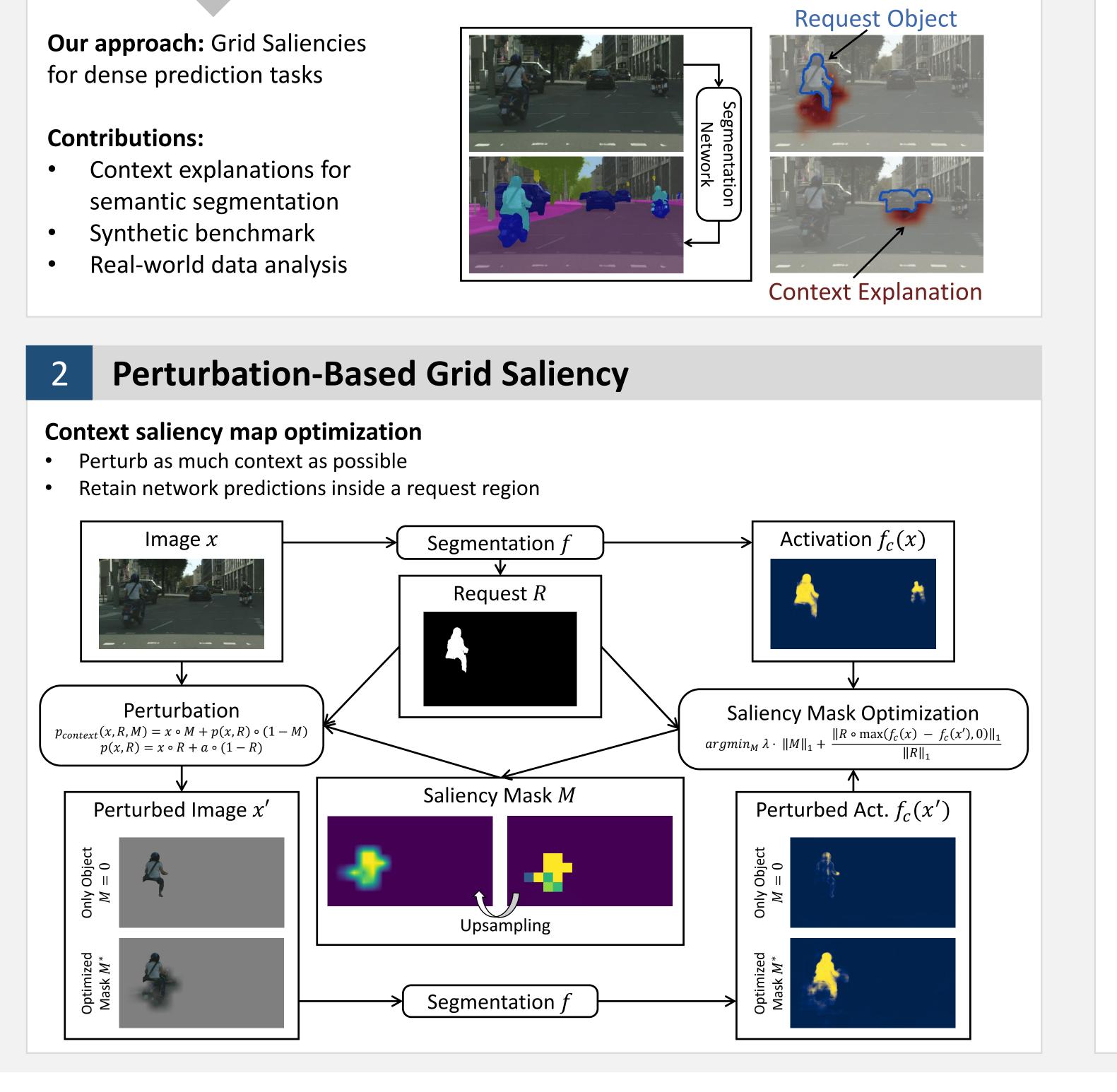
## **Grid Saliency for Context Explanations of Semantic Segmentation**

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Classification

Motivation

image classifications [1,2,3,4]

**Prior work:** Saliency maps are used for

visual explanations of neural network

## Synthetic Data for Benchmarking Saliencies Generation of dataset with induced bias MNIST digits are combined with random Context bias is induced into dataset by choosing fore- and background textures the same background texture for a specific digit Unbiased Digit 5 **MNIST** Digit Segmentation **Texture Pool** Has the network picked up the bias? Test a potentially biased network on an unbiased dataset **Predictions** Network IoU on unbiased test set for digit Strongly Drop in segmentation IoU for biased digit Network trained on: Unbiased Biased Biased → Network has picked up the bias towards digit 2 on noisy texture Can the saliency detect biased samples and localize the bias? Measure $CBD = \frac{salient\ context}{}$ biased salient context Measure CBL =salient context averaged over 5 bias textures and 5 datasets averaged over 10 bias digits, 5 bias textures, and 5 datasets Gradients [1] Gradients [4] Gradients [3] Grid Saliency Weak bias Strong bias Mean CBD for digit High grid saliency on biased context High grid saliency on biased digits → Biased samples can be detected → Bias can be localized

## **Grid Saliency on Cityscapes** Statistics on context explanations Analysis of salient context over the Cityscapes validation set Relative amount of salient context pixels for different Salient Context request classes Baseline: inflated object instances **Exemplary Findings:** Road for car Bicycle for rider Vegetation for pole Sidewalk for bicycle ■ Rider for motorcycle **Examples of context explanations Error case analysis** pedestrian $\rightarrow$ bicycle not salient as rider $\rightarrow$ arm pose salient

[3] Mukund Sundararajan et al. Axiomatic attribution for deep networks. In

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References

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[2] Ruth Fong et al. Interpretable explanations of black boxes by meaningful perturbation.