XPROAX – Local explanations for text classification with progressive neighborhood approximation

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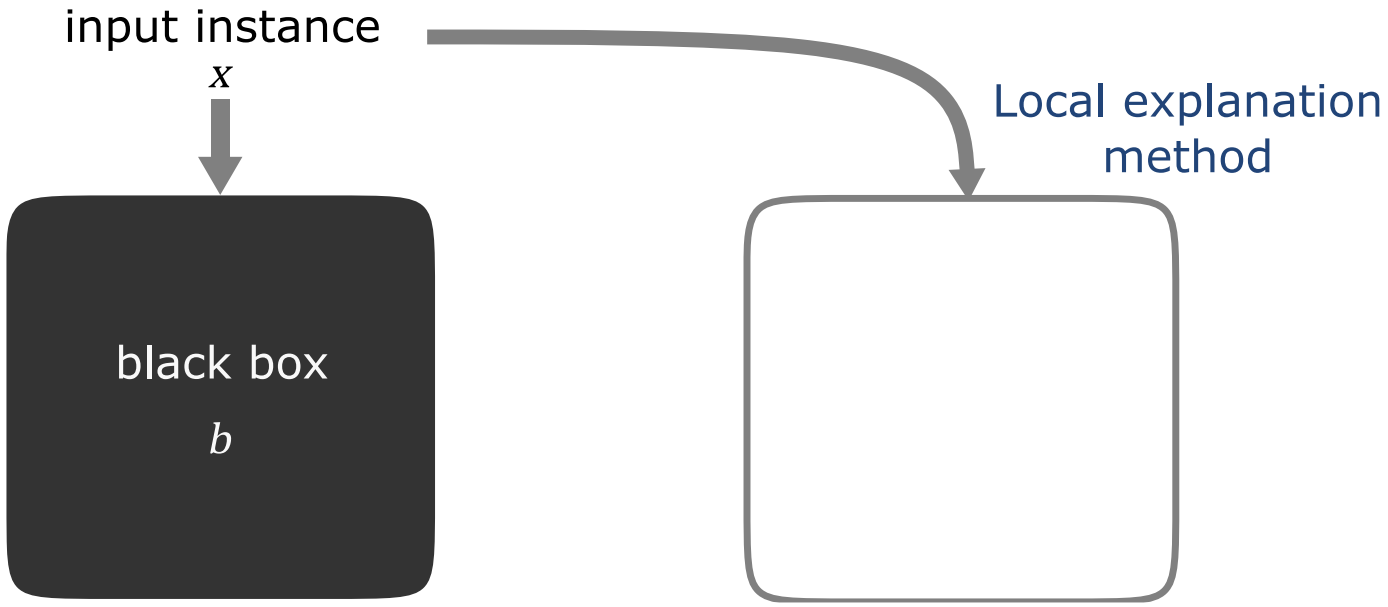
Niedersächsisches Ministerium für Wissenschaft und Kultur

Local explanation method



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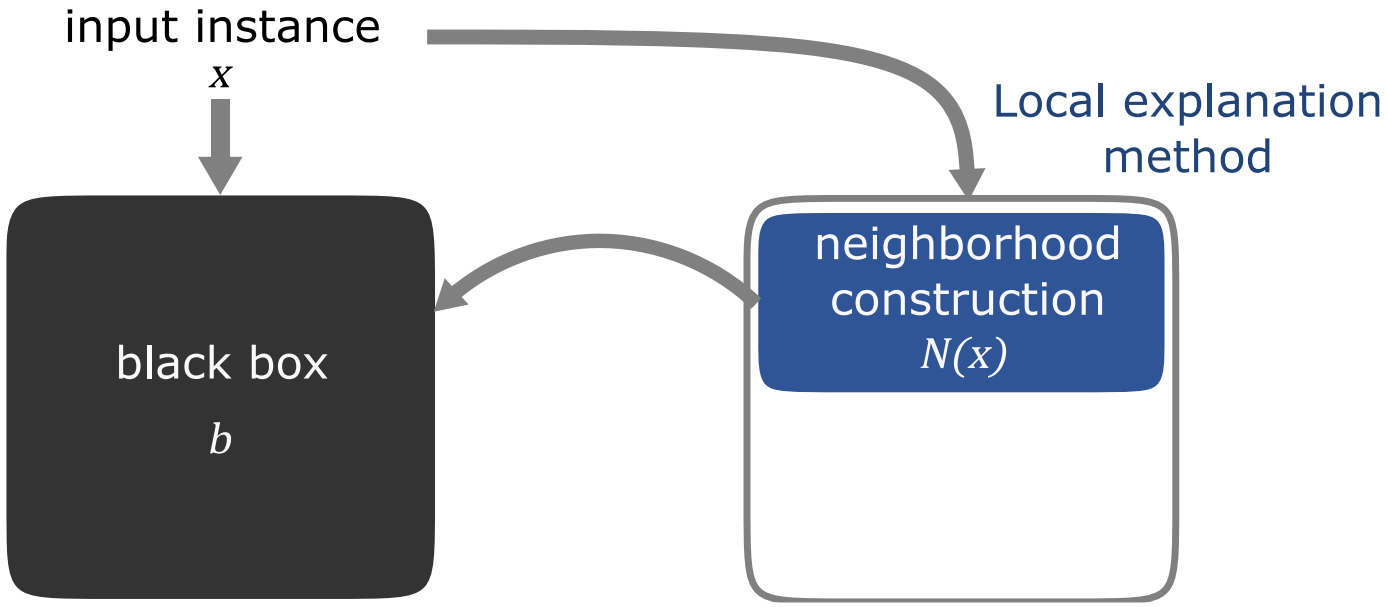

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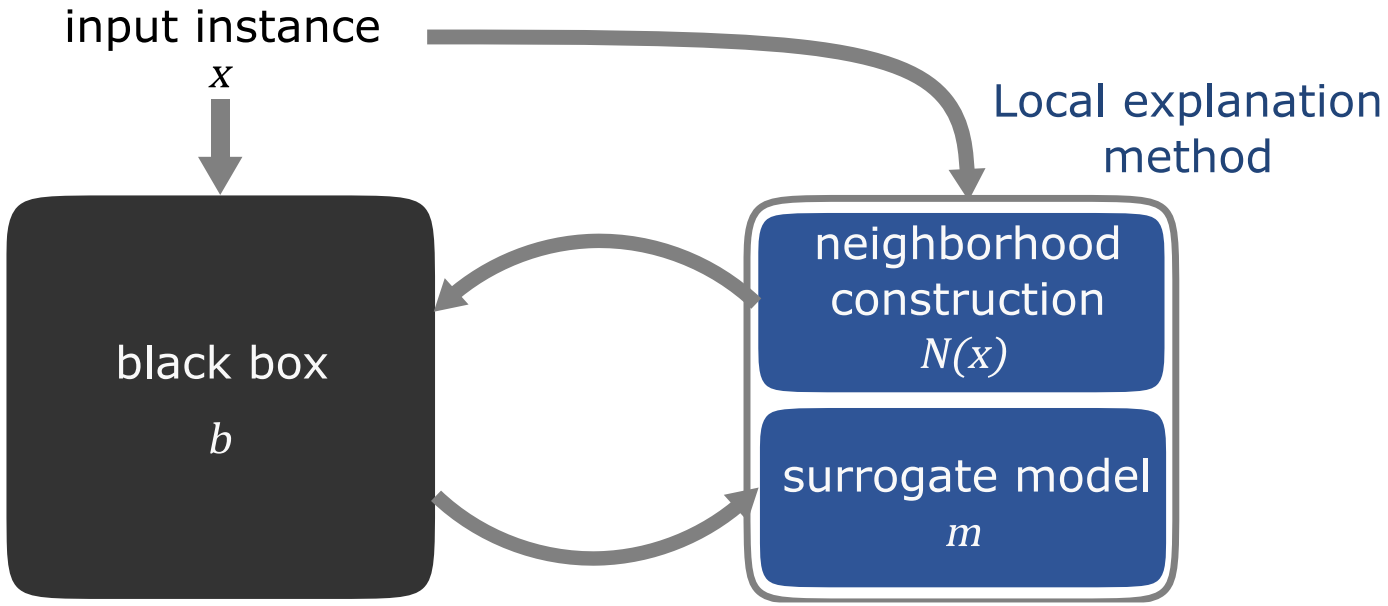

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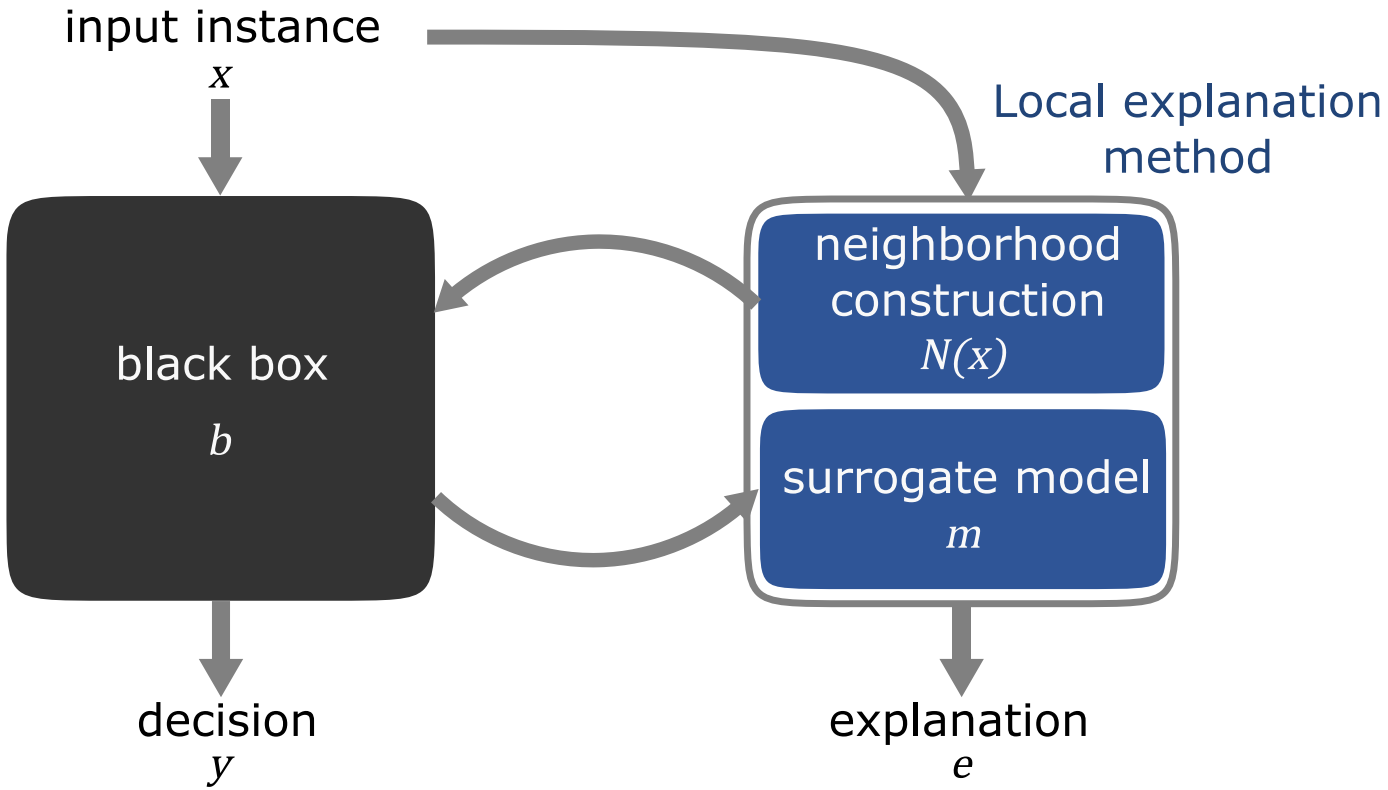
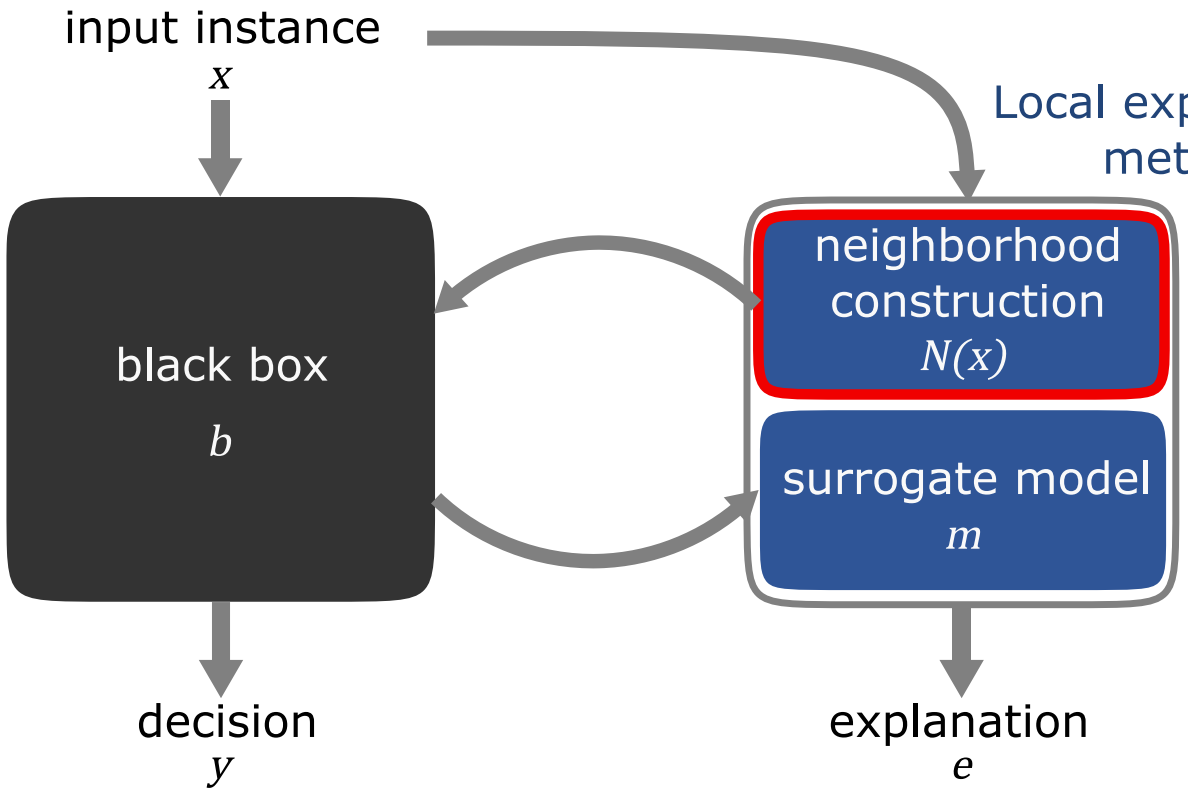


Local explanation method for text classification



What should be the neighborhood of a text?

Local explanation method for text classification

Input text: “good food.”
(Binary classification problem)

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- **Perturbation** (Word Dropping)

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  → **Incomplete sentences**

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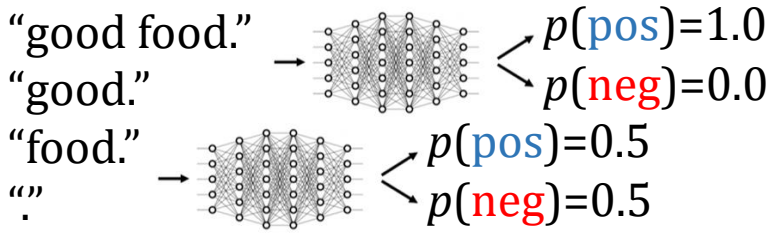

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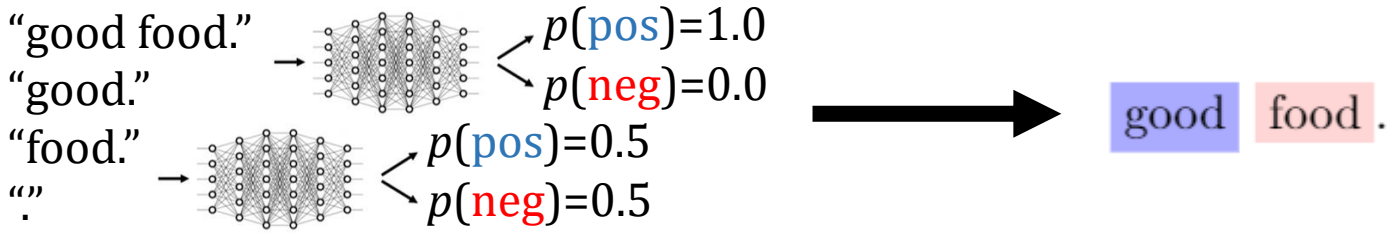

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- Construct neighborhood in **latent space**

  “good food.”
  “very good!”
  “great food.”
  “bad food.”
  “horrible food.”
  …

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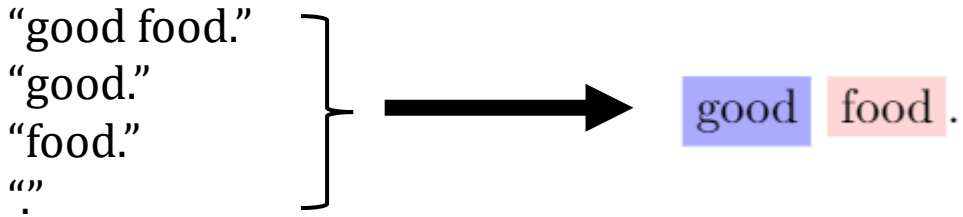

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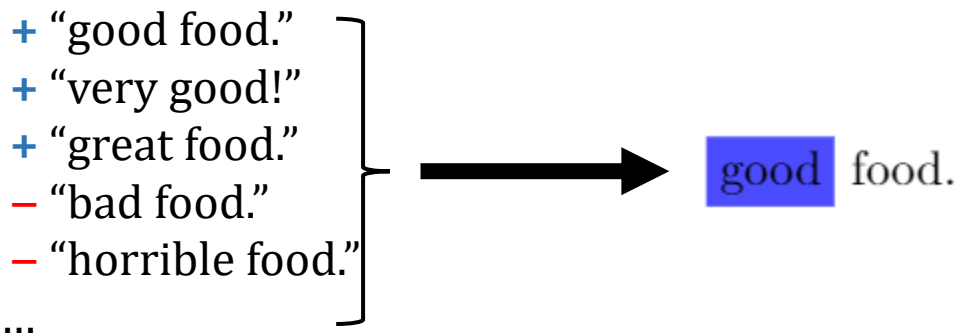
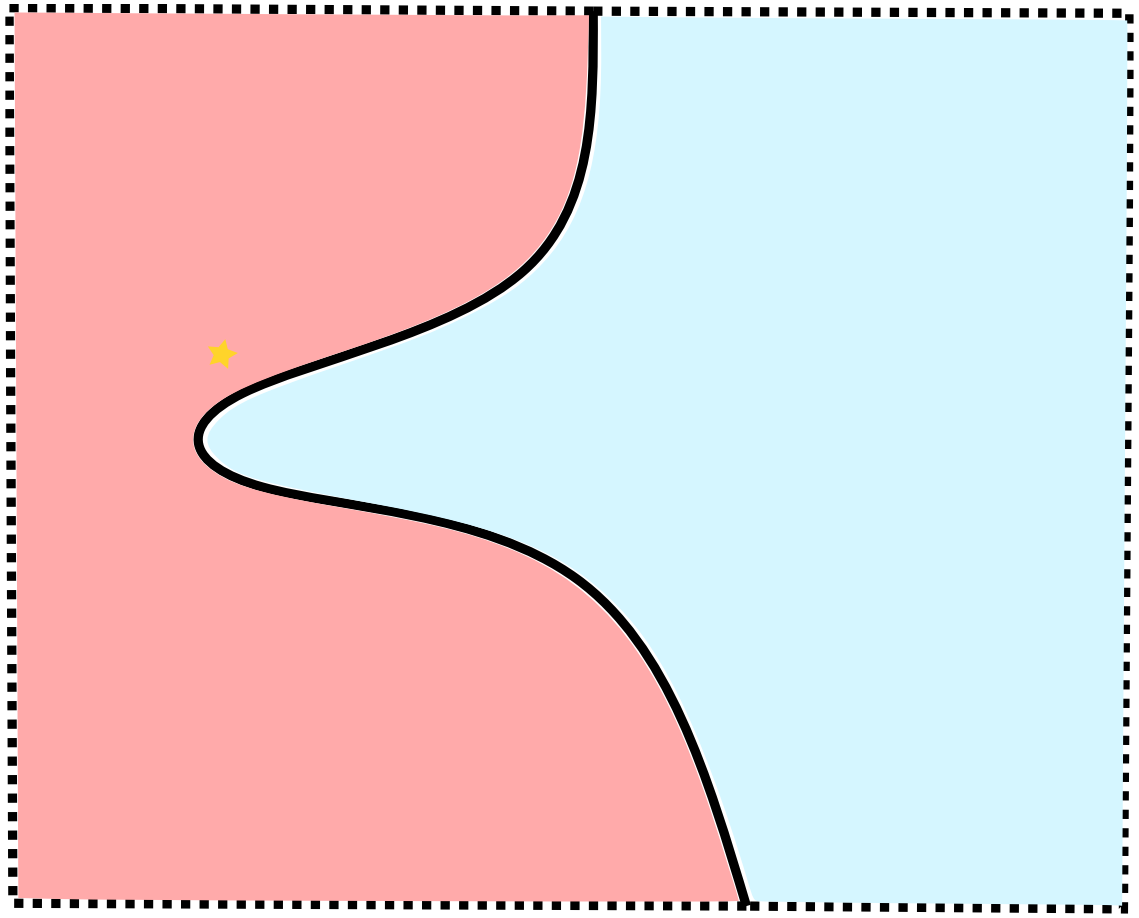


XPROAX – local eXplanation with PROgressive neighborhood ApproXimation

- How to construct a neighborhood in a high-dimensional latent space?

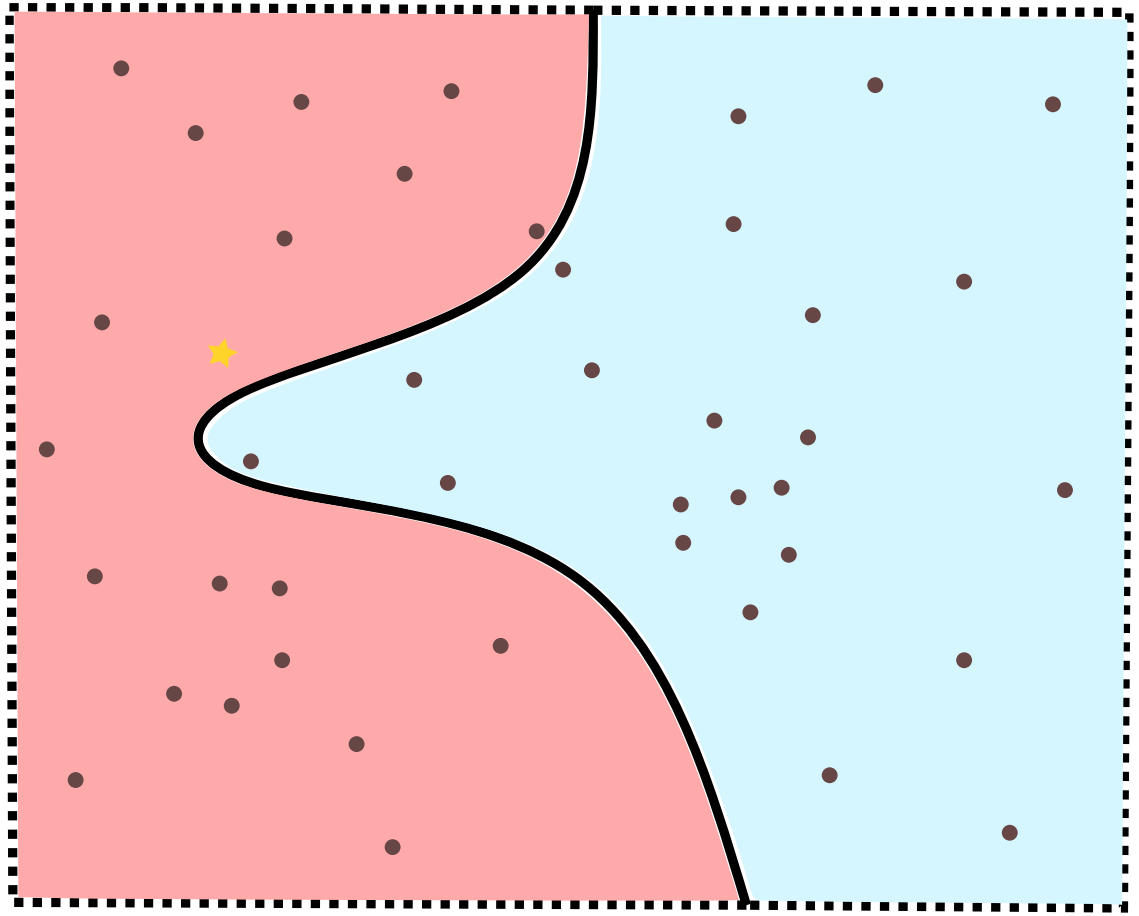
XPROAX – local eXplanation with PROgressive neighborhood ApproXimation

- Picking neighbors from a corpus as landmarks



XPROAX – local eXplanation with PROgressive neighborhood ApproXimation

- Picking neighbors (with the opposite label) from a corpus as landmarks



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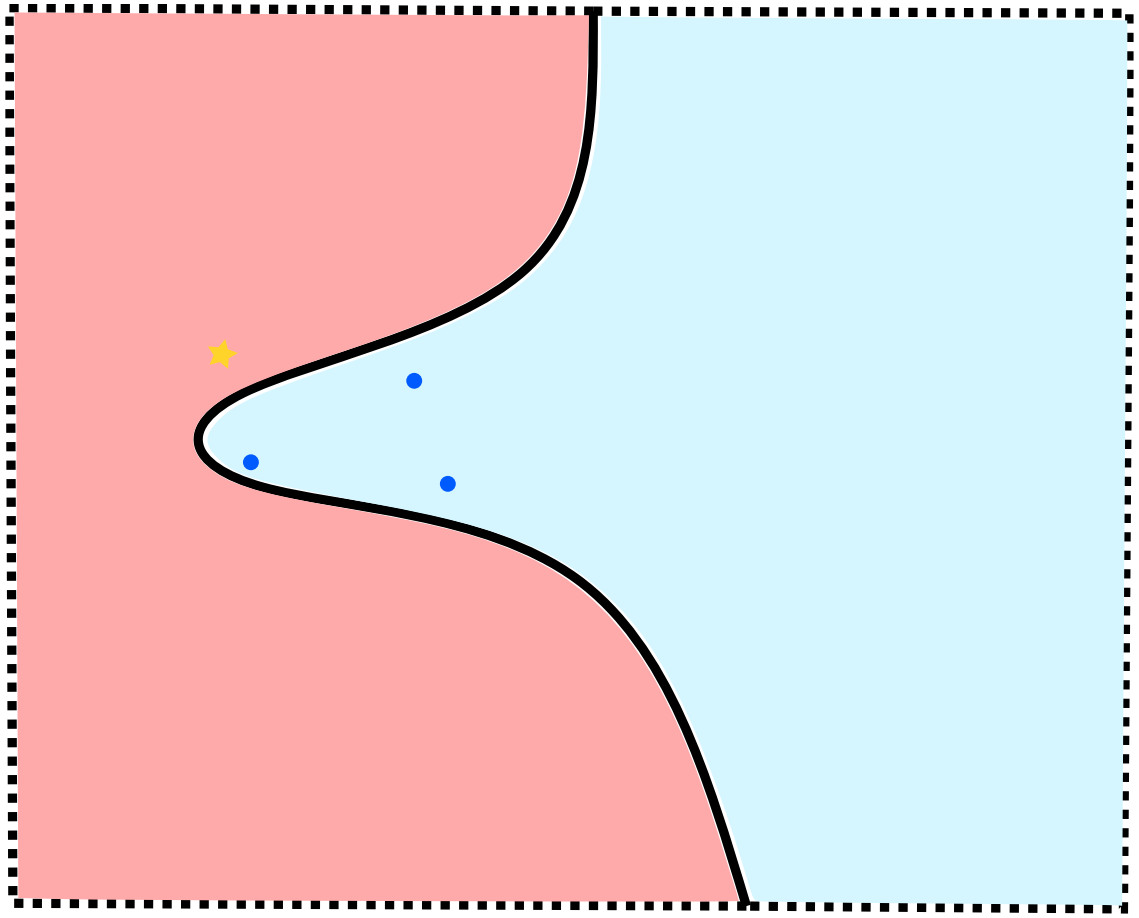

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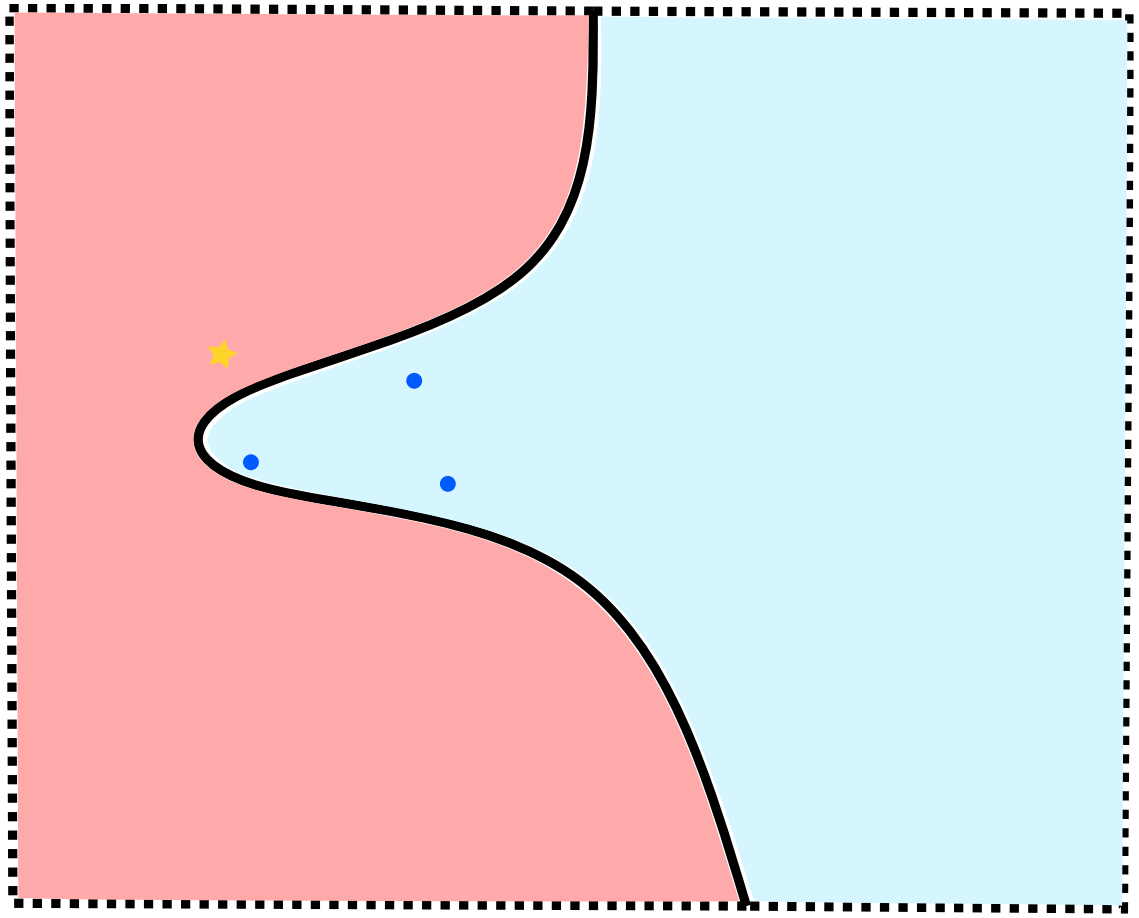
- Picking neighbors (with the opposite label) from a corpus as landmarks
- Two-staged progressive approximation

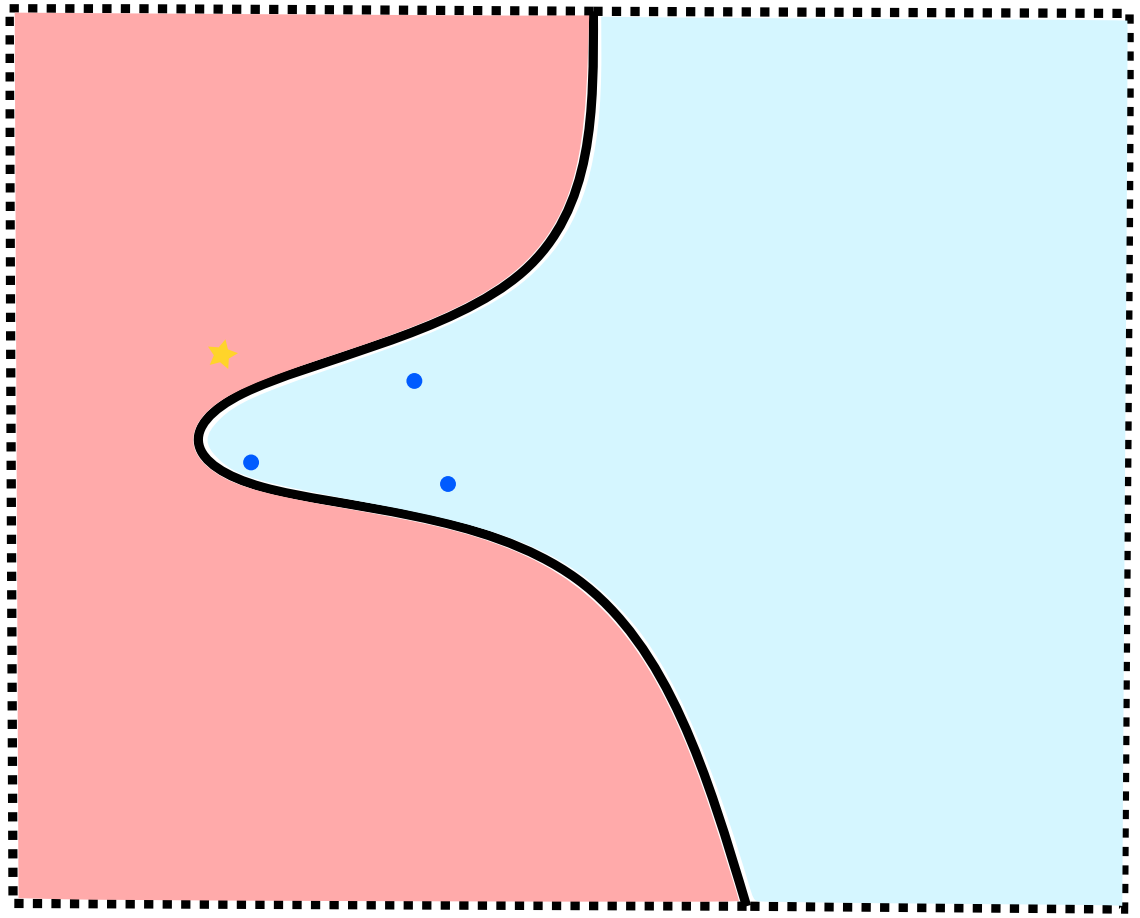


Two-staged progressive approximation

Algorithm 1 Neighborhood approximation

Input: x: query instance; C: set of counterfactual landmarks
Output: N_{new}: generated neighbors; C_{new}: updated C

$C_{new} = \emptyset$
repeat
  $z_p, z_q = \text{RandomlyDraw}(C, 2)$
    # draw randomly 2 vectors from the landmark set
  $Z' = I(z_p, z_q)$
      # 1st interpolation: between counterfactuals
  $Z = \emptyset$
  for $z_i \in Z'$ **do** *# 2nd interpolation: between polarities*
    if $b(D(z_i)) \neq b(x)$ **then**
      $Z \leftarrow Z + I(z_i, E(x))$
    end if
  end for
  $z_c = \text{ClosestCounterfactual}(Z, 1)$
  $C_{new}.insert(z_c)$
  $N_{new} \leftarrow N_{new} + D(Z)$
until k times
return N_{new}, C_{new}



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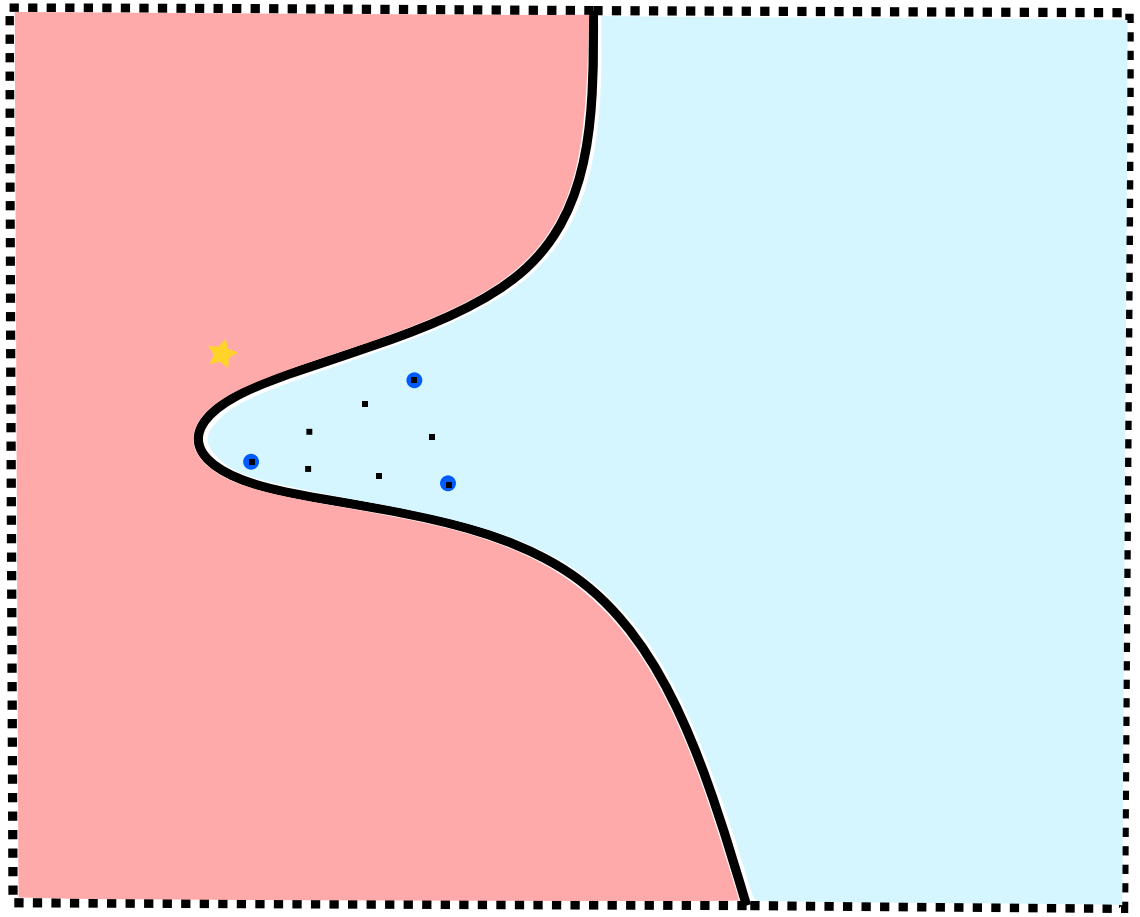

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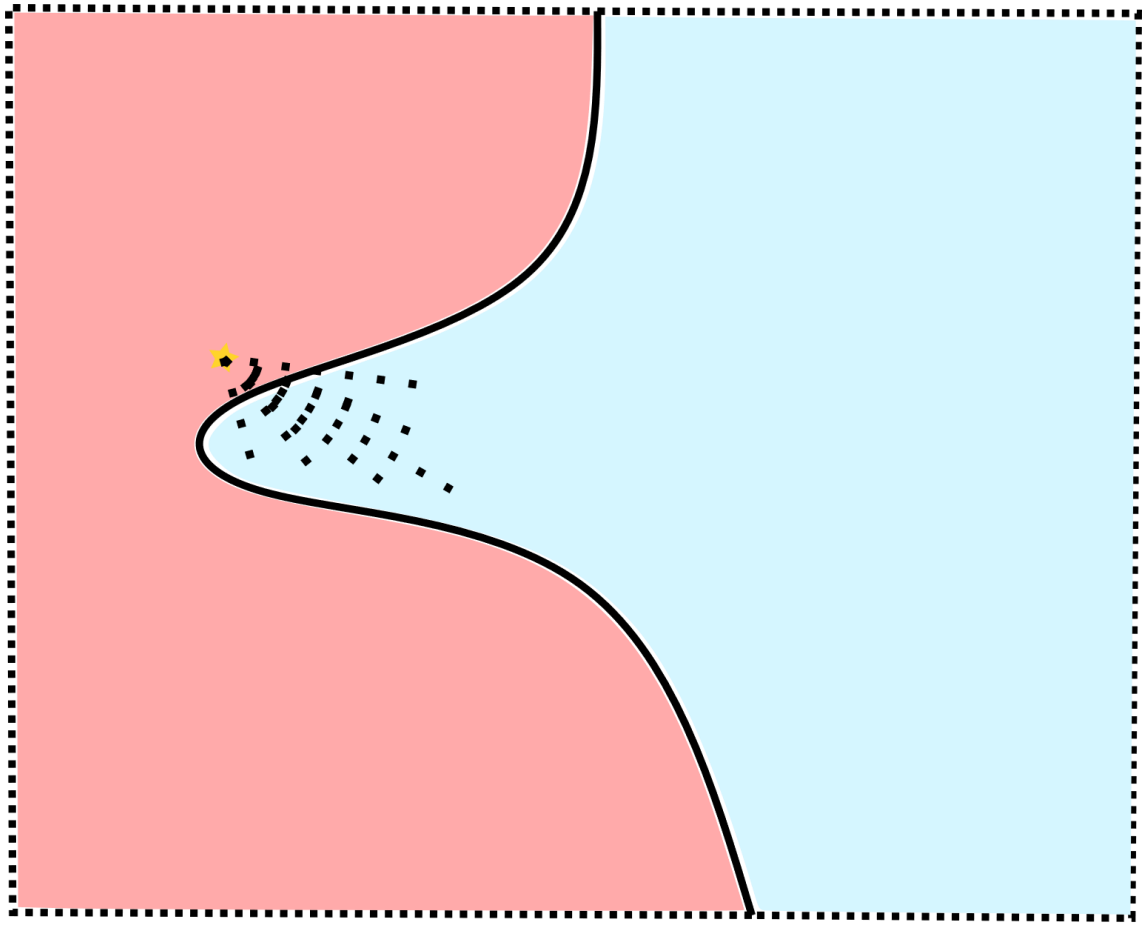

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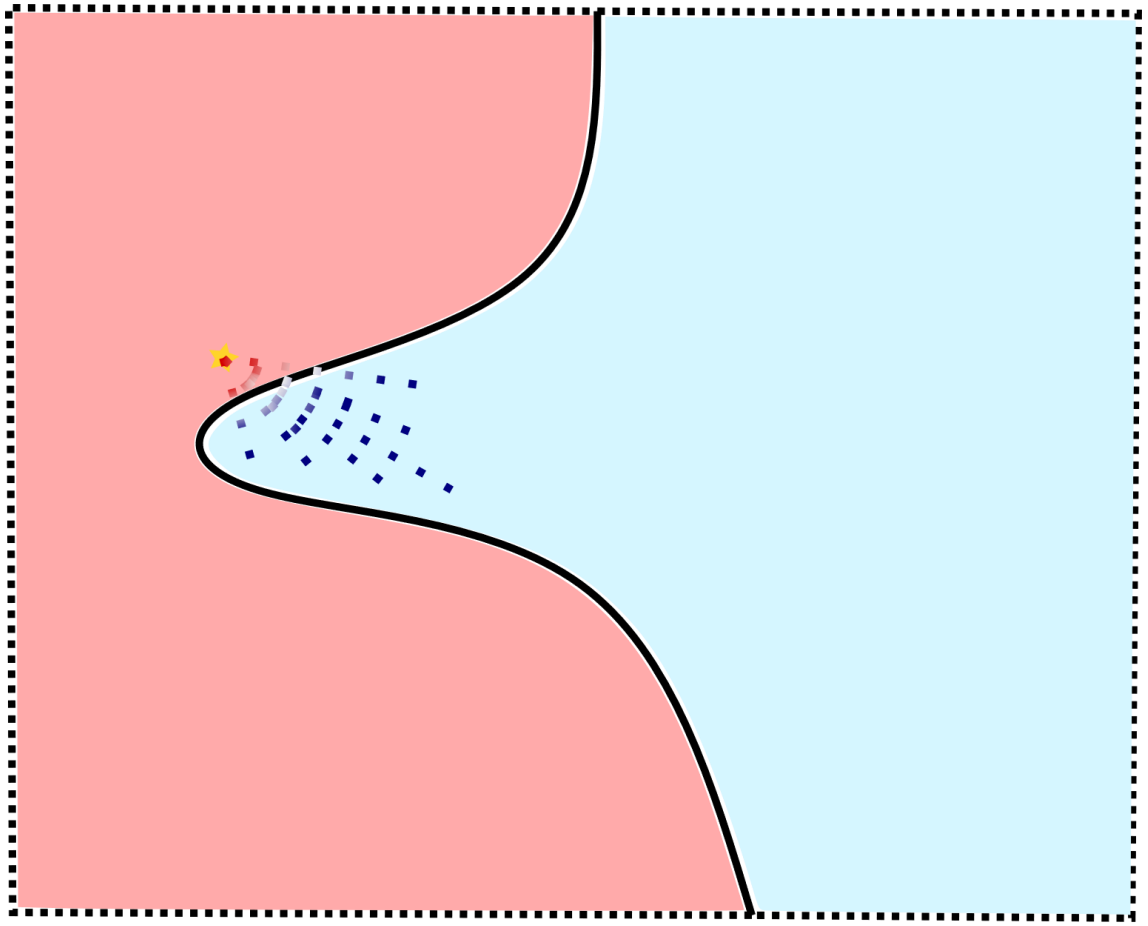

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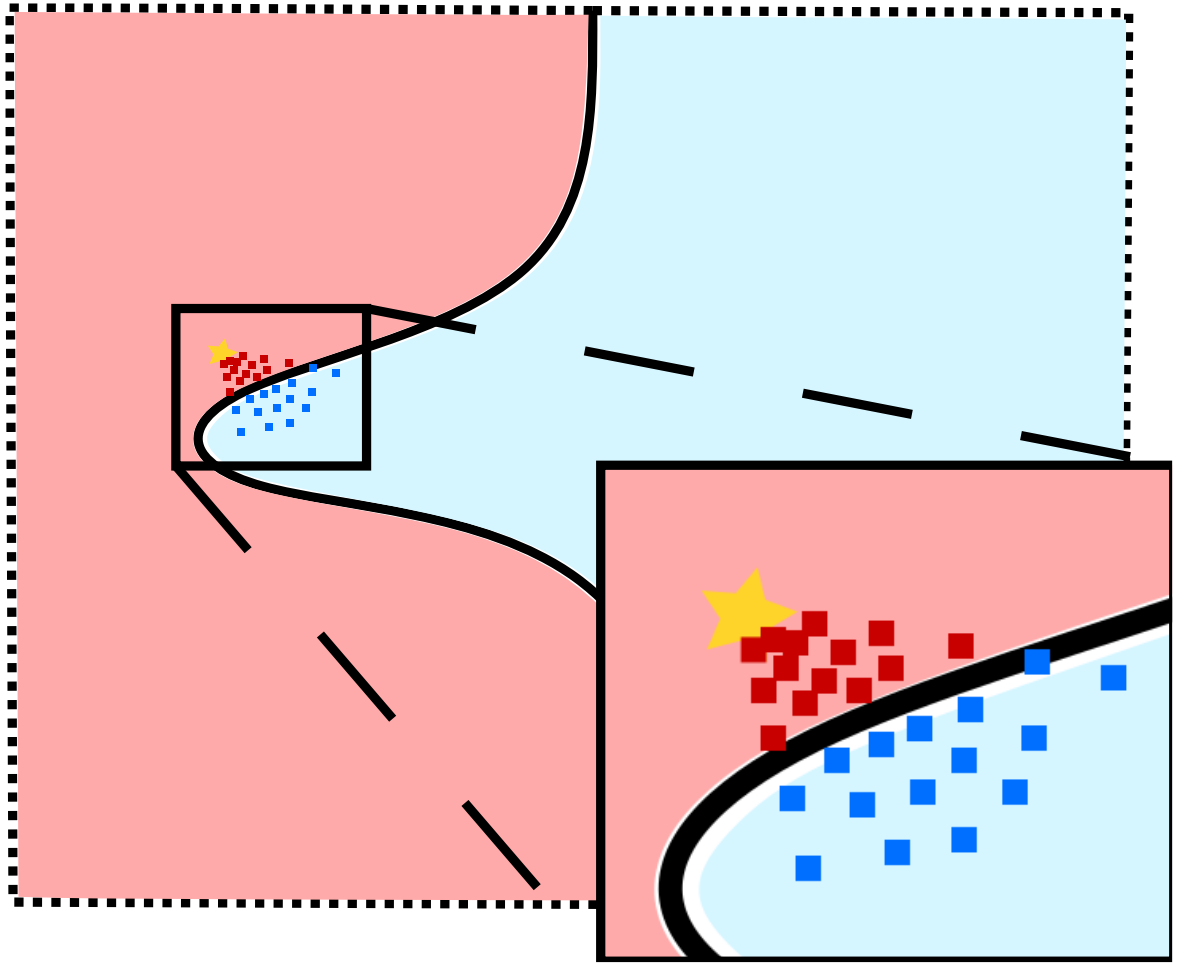

Experimental results

Competitors:

- **LIME**: applies word dropping to the input text for the neighborhood construction
- **XSPELLS**: deploys a generative autoencoder and performs random sampling in the latent space

Experimental results

Dataset: **Yelp**, Black box model $b(\cdot)$: **DNN**

Input Text	$b(\cdot)$	XPROAX	LIME	XSPELLS[a]
great food.	**1.00**	great 0.69 food 0.05	great 0.70 food -0.24	food 0.11 italian* 0.08
great sushi.	**0.99**	great 0.62 sushi 0.12	great 0.56 sushi -0.11	salsa 0.17 guys 0.14
great pizza.	**1.00**	great 0.70 pizza 0.01	great 0.73 pizza -0.27	good 0.14 food 0.08
great beer.	**1.00**	great 0.64 beer 0.02	great 0.73 beer -0.27	good 0.15 story* 0.07

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Experimental results

Input 2	fries are n't worth coming back .	Random Forest $b(\cdot)$: **positive**, Dataset: **Yelp**
XPROAX	**Saliency**: fries are n't worth coming back . **Factuals**: 1) the fries were n't worth coming. 2) _unk_[b] are n't worth going back. 3) the fries were worth coming back. 4) the fries were worth going back. 5) you do n't be worth coming.	**Extrinsic words**[a]: not perfect **Counterfactuals**: 1) _unk_ do n't bother in back. 2) _unk_ do n't bother going back. 3) _unk_ do n't be anybody back. 4) a few fries were definately coming back. 5) _unk_ do n't be anybody.
XSPELLS	**Factuals**: 1) it seems well they did 2) and i feel like on service 3) dave is excellent 4) everything we will get 5) all i hung up is nice **Common words in factuals**: seems (0.091), well (0.091), feel (0.091)	**Counterfactuals**: 1) both to die 2) all else s 3) every i may 4) who makes me money last 5) all were nt pricey **Common words in counterfactuals**: die (0.111), else (0.111), every: (0.111)
LIME	**Saliency**: fries are n't worth coming back .	

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- Detailed explanations for better understanding

Thank you for listening!

Authors: **Yi Cai**, **Arthur Zimek**, **Eirini Ntoutsi**

Contact: **cai@l3s.de**

Code: **https://github.com/caiy0220/XPROAX**

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