

GENERALIZED INVERSE CLASSIFICATION

SDM '17

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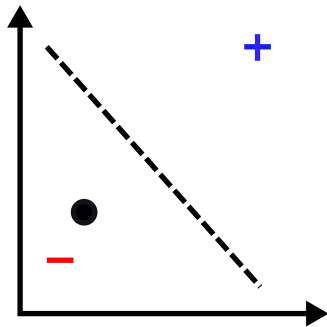


What is *inverse classification*?

- The process of making **meaningful perturbations** to a test instance such that the probability of a desirable outcome is maximized.

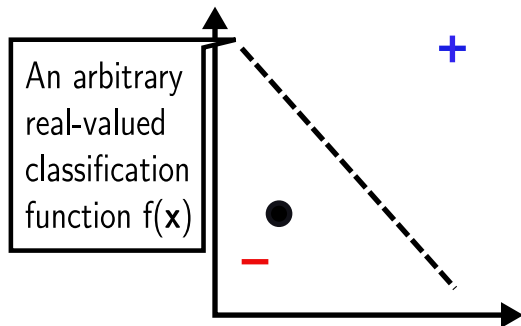
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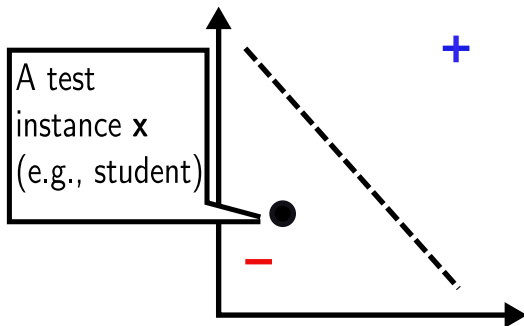
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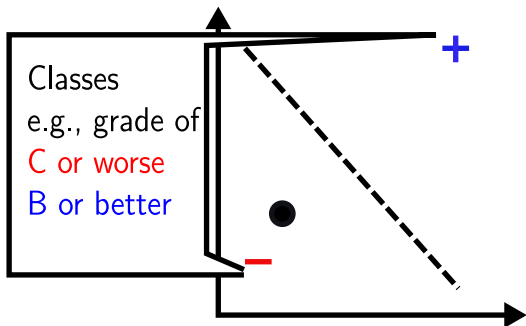
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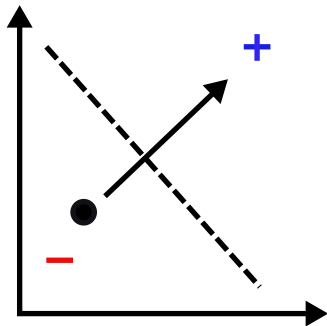
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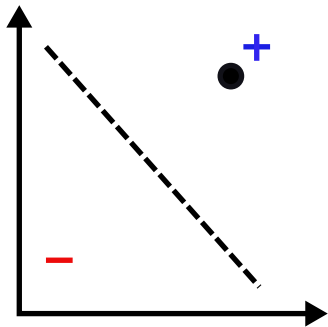
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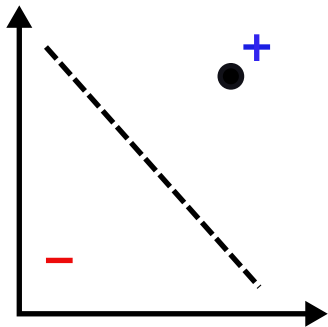
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What about the **meaningful** part of the definition?

Well...lets visit some past work!

- Michael T. Lash, Qihang Lin, W. Nick Street, and Jennifer G. Robinson, “A budget-constrained inverse classification framework for smooth classifiers”, *arXiv preprint arXiv:1605.09068*, submitted.

$$\min_{\mathbf{x}} f(\mathbf{x})$$

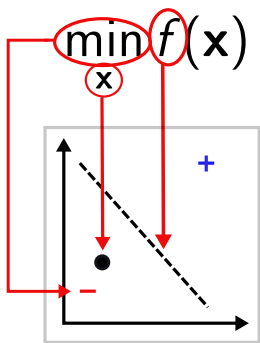
Begin with a basic formulation.

Meaningful Perturbations

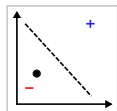
$$\min_{\mathbf{x}} f(\mathbf{x})$$

[For now] A differentiable
classification function
e.g., logistic regression,
SVM, ANN, etc.

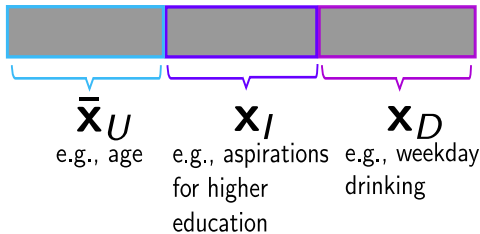
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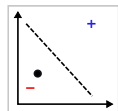


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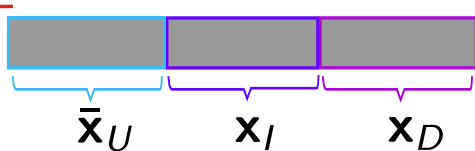


Segment features.

Meaningful Perturbations



$$\min_{\mathbf{x}} f(\mathbf{x})$$



$$H(\bar{\mathbf{x}}_U, \mathbf{x}_D)$$

Some regressor

$$H : \mathbb{R}^{|\mathcal{U}|+|\mathcal{D}|} \rightarrow \mathbb{R}^{|\mathcal{I}|}$$

Estimate indirectly changeable.

$$\begin{aligned} \min_{\mathbf{x}_D} & f(\bar{\mathbf{x}}_U, H(\bar{\mathbf{x}}_U, \mathbf{x}_D), \mathbf{x}_D) \\ \text{s.t.} & \phi(\mathbf{x}_D - \bar{\mathbf{x}}_D) \leq B \\ & l_i \leq x_i \leq u_i \text{ for } i \in D \end{aligned}$$

Update objective function. Add constraints.

Meaningful Perturbations

$$\min_{\mathbf{x}_D} f(\bar{\mathbf{x}}_U, H(\bar{\mathbf{x}}_U, \mathbf{x}_D), \mathbf{x}_D)$$

$$\text{s.t. } \phi(\mathbf{x}_D - \bar{\mathbf{x}}_D) \leq B$$

$$l_i \leq x_i \leq u_i \text{ for } i \in D$$

$$\phi(\mathbf{z}) = \sum_{i \in D} c_i^+ (z_i)_+ + c_i^- (z_i)_-$$

Cost-change function

Meaningful Perturbations

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Bounds

1. Relax assumptions about $f(\cdot)$.

$$\min_{\mathbf{x}_D} f(\bar{\mathbf{x}}_U, H(\bar{\mathbf{x}}_U, \mathbf{x}_D), \mathbf{x}_D)$$

$$\text{s.t. } \phi(\mathbf{x}_D - \bar{\mathbf{x}}_D) \leq B$$

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Assume:

- $f(\mathbf{z})$ differentiable
- $\|\nabla f(\mathbf{z}) - \nabla f(\mathbf{z}')\| \leq L \|\mathbf{z} - \mathbf{z}'\|$, $\mathbf{z}, \mathbf{z}' \in \mathbb{R}^{|D|}$

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Assume:

- $f: \mathbb{R}^p \rightarrow \mathbb{R}$

Main Contributions

1. Relax assumptions about $f(\cdot)$.
2. Quadratic cost-change function.

$$\min_{\mathbf{x}_D} f(\bar{\mathbf{x}}_U, H(\bar{\mathbf{x}}_U, \mathbf{x}_D), \mathbf{x}_D)$$

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1. Relax assumptions about $f(\cdot)$.
2. Quadratic cost-change function.
3. Three real-valued heuristic optimization methods and two sensitivity analysis-based optimization methods.
 - * Projection operator to maintain feasibility.

Heuristic

- Hill Climbing + Local Search (HC+LS)
- Genetic Algorithm (GA)
- Genetic Algorithm + Local Search (GA+LS)

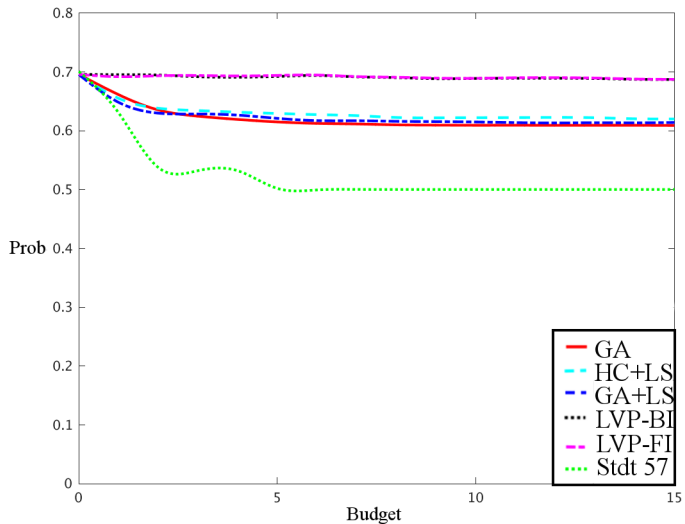
Sensitivity Analysis

- Local Variable Perturbation – First Improvement (LVP-FI)
- Local Variable Perturbation – Best Improvement (LVP-BI)

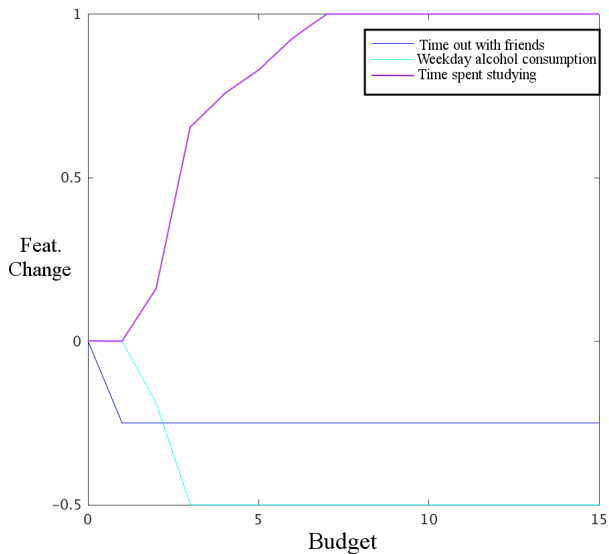
Experiment Decisions and Data

- $f(\cdot)$: Random forest
- $H(\cdot)$: Kernel regression
- Dataset 1: Student Performance (UCI Machine Learning Repository).
- Dataset 2: ARIC
- One f for optimization, separate f for heldout evaluation.

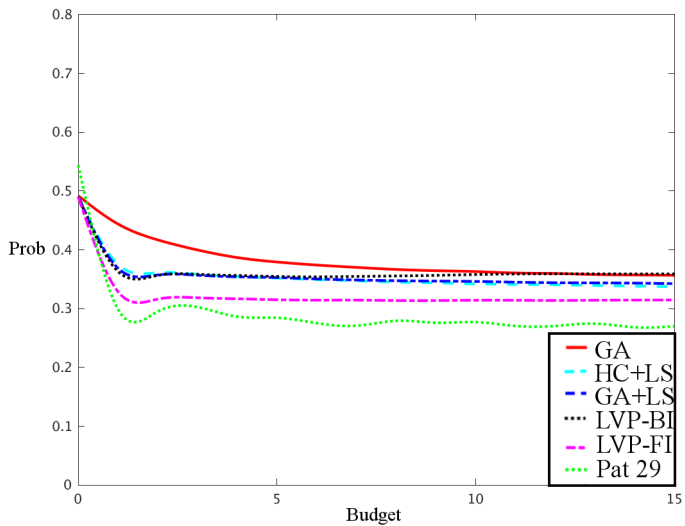
Results: Student Performance



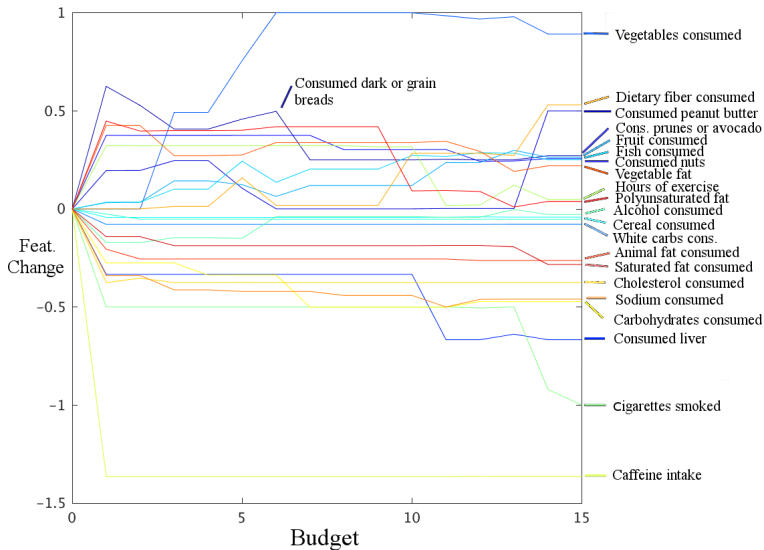
Results: Student Performance



Results: ARIC



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Need sparsity constraints

Conclusions

- **Generalized** Inverse Classification: can use virtually any learned f (as shown by experiments w/ Random Forest classifier).
- Our proposed methods were successful, although this varied by dataset.

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- Future work will focus on incorporating causal methodology...