Strategic Classification in the Dark

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(supported by the European Union's Horizon 2020 research and innovation program under grant agreement No 682203 -ERC-[Inf-Speed-Tradeoff])







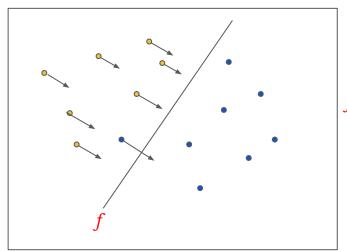






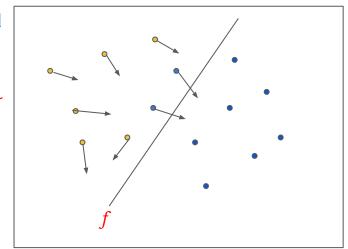
Ganesh Ghalme, Itay Eilat, Inbal Talgam-Cohen, Nir Rosenfeld

Main Idea



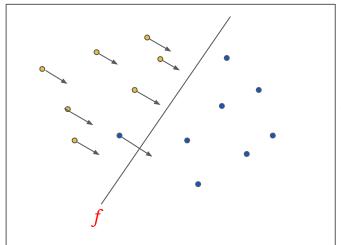
- Loan approved
- Loan denied

f: Bank's classifier



Strategic behaviour of users, dependent on its cost function, for a transparent strategic classifier Strategic behaviour, dependent on its cost function, for an opaque strategic classifier (users in dark)

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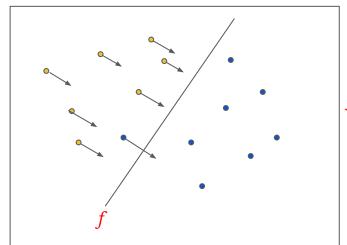
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Users moves strategically as per its learnt classifier

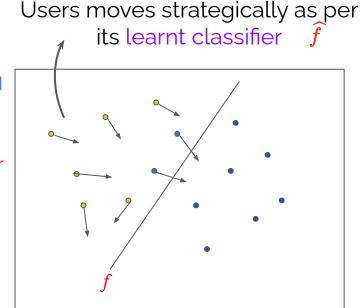
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Objective: Compare the classification errors of transparent and opaque strategic classifiers

Main Contribution

- Price of OPacity (POP): Difference between the errors of opaque and transparent strategic classifiers.
 - POP > 0 implies transparency prevails.
- A sufficient condition for POP > 0 which we show is also necessary in some cases.
 - The sufficiency condition depends on the probability mass of the enlargement set (defined next).

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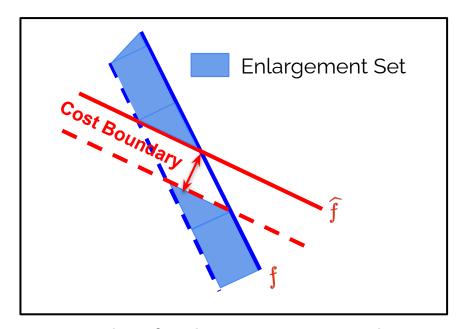
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 - The sufficiency condition depends on the probability mass of the enlargement set (defined next).
 - We demonstrate the utility of these results by analyzing a normally distributed population classified linearly and show that POP can become arbitrarily large.
- Experiments on synthetic as well as a large dataset on loan requests show that POP can be quite large in practice.

Enlargement Set

- The set of users that were classified differently by f because of opacity.
- We show that even small differences between f and f could result in a large probability mass on the enlargement set.



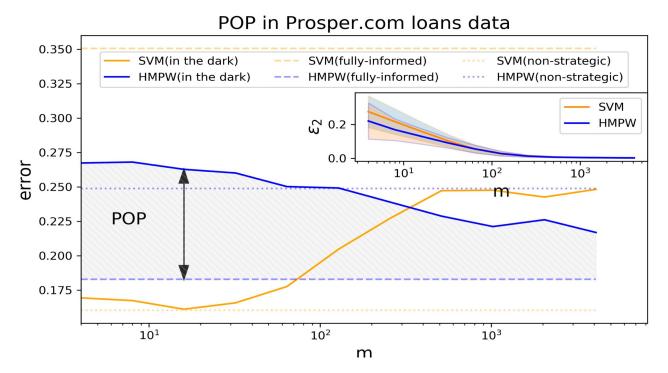
Example of Enlargement Set when f and \hat{f} are linear classifiers

Enlargement Set (Contd.)

- We show a sufficient condition on the probability mass of the enlargement set for POP > 0.
 - The sufficient condition depends on the errors of the optimal classifier for the system and the system's classifier f.

- From the user's perspective, the enlargement set is undesirable.
 - Under opacity these users are classified negatively, whereas under transparency they would have been classified positively.

Experiment showing positive POP



m is the number of samples for learning \widehat{f}

Key Takeaways

 The System cannot guarantee higher payoff by keeping the users in the dark.

• Even small errors in estimating f by users in dark could result in a big enlargement set implying POP > 0.

 Under an opaque policy Users with access to more samples have greater likelihood of being classified accurately than those with access to fewer samples.

Thank You!