Support Vector Machines for Uplift Modeling

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What is uplift modeling?

From workshop's description:

> *Traditionally, causal relationships are identified based on controlled experiments. [...] there has been an increasing interest in discovering causal relationships from observational data only.*

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> *Traditionally, causal relationships are identified based on controlled experiments. [...] there has been an increasing interest in discovering causal relationships from observational data only.*

- Suppose we do have data from a controlled experiment
- Question: what can Machine Learning do for us?

- Relatively little interest in the ML community

What is uplift modeling?

Uplift modeling

- Given two training datasets:
  1. the treatment dataset
     individuals on which an action was taken
  2. the control dataset
     individuals on which no action was taken
     used as background
- Build a model which predicts the causal influence of the action on a given individual

Uplift modeling

Notation:

- P^T probabilities in the treatment group
- P^C probabilities in the control group

Traditional classifiers predict the conditional probability

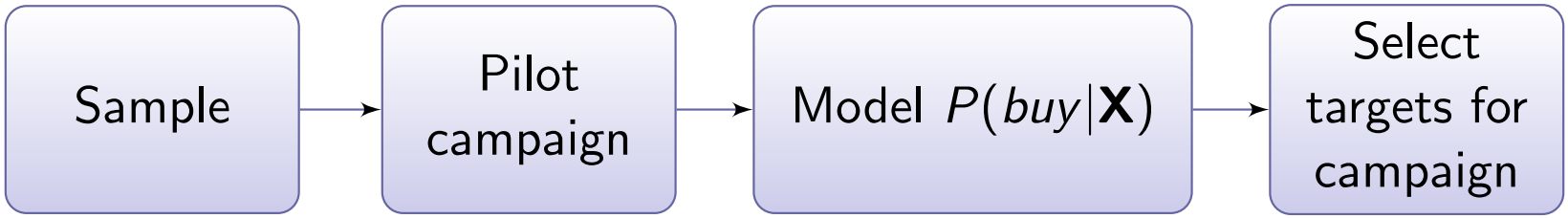
$$P^T(Y \mid X_1, \ldots, X_m)$$

Uplift models predict change in behaviour resulting from the action

$$P^T(Y \mid X_1, \ldots, X_m) - P^C(Y \mid X_1, \ldots, X_m)$$

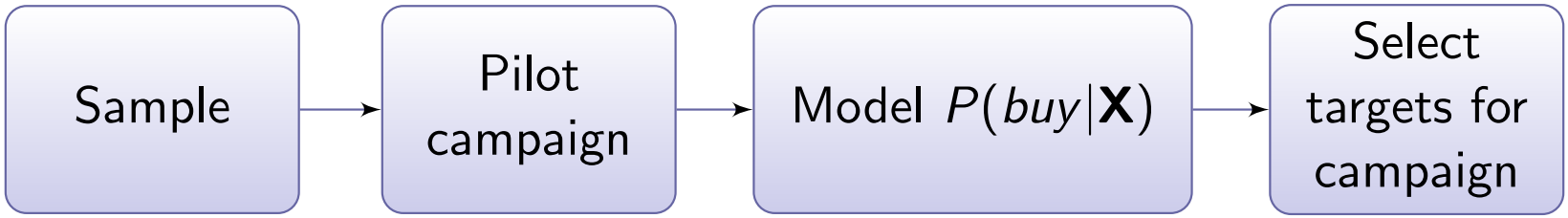
Why uplift modeling?

A typical marketing campaign



Why uplift modeling?

A typical marketing campaign



- But this is not what we need!

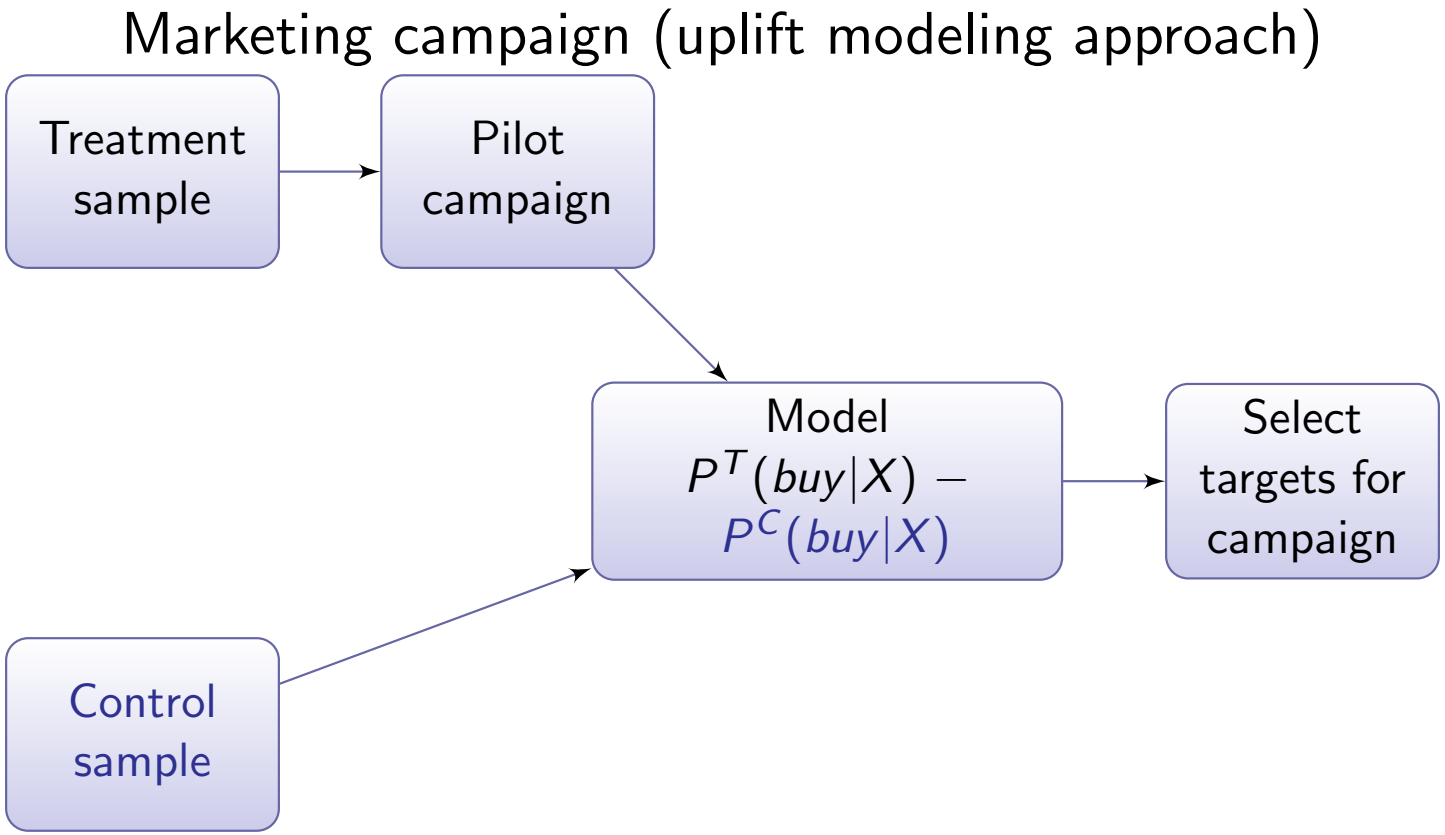
- We want people who bought because of the campaign
- Not people who bought after the campaign

A typical marketing campaign

We can divide potential customers into four groups

1. Responded **because** of the action (**the people we want**)
2. Responded, but would have responded **anyway** (**unnecessary costs)**
3. Did not respond and the action had **no impact** (**unnecessary costs**)
4. Did not respond **because** the action had a (**negative impact**)

Marketing campaign (uplift modeling approach)



Applications in medicine

- A typical medical trial:
  - treatment group: gets the treatment
  - control group: gets placebo (or another treatment)
  - do a statistical test to show that the treatment is better than placebo
- With uplift modeling we can find out for whom the treatment works best
- Personalized medicine

Main difficulty of uplift modeling

- Rubin's causal inference framework

The fundamental problem of causal inference

- Our knowledge is always incomplete
- For each training case we know either
  - what happened after the treatment, or
  - what happened if no treatment was given
- Never both!

- This makes designing uplift algorithms challenging

The two model approach

An obvious approach to uplift modeling:

1. Build a classifier M^T modeling $P^T(Y|\mathbf{X})$ on the treatment sample
2. Build a classifier M^C modeling $P^C(Y|\mathbf{X})$ on the control sample
3. The uplift model subtracts probabilities predicted by both classifiers

$$M^U(Y|\mathbf{X}) = M^T(Y|\mathbf{X}) - M^C(Y|\mathbf{X})$$

Two model approach

Advantages:

- Works with existing classification models
- Good probability predictions $\Rightarrow$ good uplift prediction

Disadvantages:

- Differences between class probabilities can follow a different pattern than the probabilities themselves
  - each classifier focuses on changes in class probabilities but ignores the weaker 'uplift signal'
  - algorithms designed to focus directly on uplift can give better results

Uplift Support Vector Machines

Uplift Support Vector Machines

- Support Vector Machines (SVMs) are a popular Machine Learning algorithm
- Here we adapt them to the uplift modeling problem

Uplift Support Vector Machines

- Recall that the outcome of an action can be
  - positive
  - negative
  - neutral

Uplift Support Vector Machines

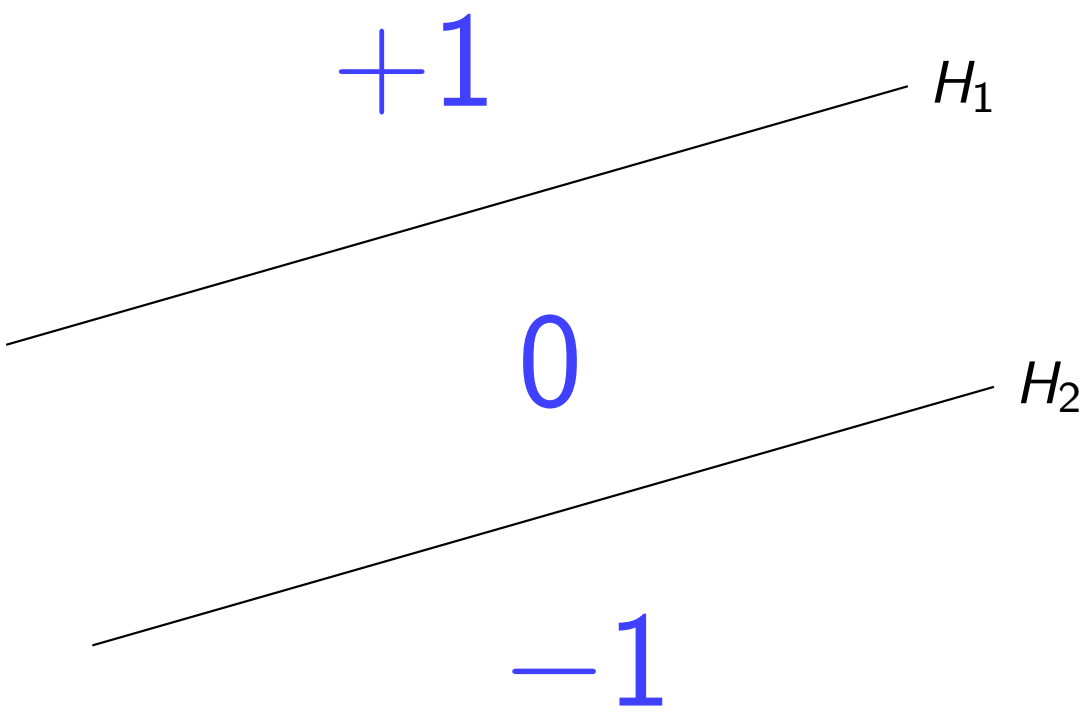
- Recall that the outcome of an action can be
  - positive
  - negative
  - neutral

Main idea

Use two parallel hyperplanes dividing the sample space into three areas:

- positive $(+1)$
- neutral (0)
- negative (-1)

Uplift Support Vector Machines



$$H_1 : \langle \mathbf{w}, \mathbf{x} \rangle + b_1 = 0$$
$$H_2 : \langle \mathbf{w}, \mathbf{x} \rangle + b_2 = 0$$

Uplift Support Vector Machines

- How do we train Uplift SVMs?
- Classical SVMs:

  need to know if a case is classified correctly

- Fundamental problem of causal inference

  $\Rightarrow$ We never know if a point was classified correctly!
- The algorithm must use only the information available

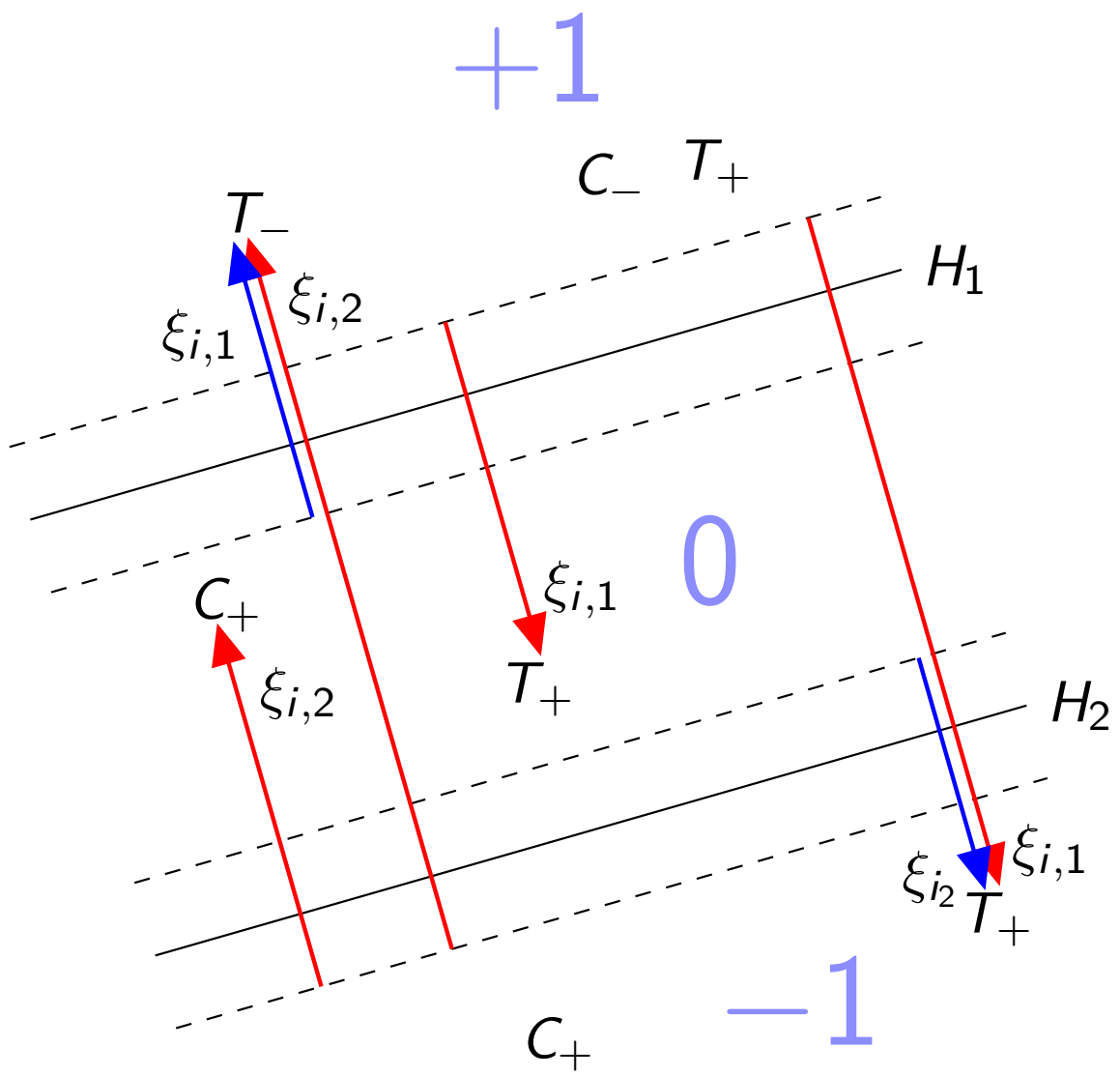
Uplift Support Vector Machines

- Four types of points: T_+, T_-, C_+, C_-
- Positive area (+1):
  - T_-, C_+ definitely misclassified
  - T_+, C_- may be correct, at worst neutral
- Negative area (-1):
  - T_+, C_- definitely misclassified
  - T_-, C_+ may be correct, at worst neutral
- Neutral area (0):
  - all predictions may be correct or incorrect

Uplift Support Vector Machines – problem formulation

- Penalize points separately for being on the wrong side of each hyperplane
- Points in the neutral area are penalized for crossing one hyperplane
  - this prevents all points from being classified as neutral
- Points which are definitely misclassified are penalized for crossing two hyperplanes
  - such points should be avoided, thus the higher penalty
- Other points are not penalized

Uplift Support Vector Machines – problem formulation



Optimization task – primal form

$$\min_{\mathbf{w},b_1,b_2\in\mathbb{R}^{m+2}} \frac{1}{2}\langle \mathbf{w},\mathbf{w}\rangle + C_1 \sum_{\mathbf{D}_+^T\cup\mathbf{D}_-^C} \xi_{i,1} + C_2 \sum_{\mathbf{D}_-^T\cup\mathbf{D}_+^C} \xi_{i,1} + C_2 \sum_{\mathbf{D}_+^T\cup\mathbf{D}_-^C} \xi_{i,2} + C_1 \sum_{\mathbf{D}_-^T\cup\mathbf{D}_+^C} \xi_{i,2},$$

subject to:

$$\begin{aligned}
\langle \mathbf{w},\mathbf{x}_i\rangle + b_1 &\leq -1+\xi_{i,1}, \text{ for } (\mathbf{x}_i,y_i)\in \mathbf{D}_+^T\cup\mathbf{D}_-^C,\\
\langle \mathbf{w},\mathbf{x}_i\rangle + b_1 &\geq +1-\xi_{i,1}, \text{ for } (\mathbf{x}_i,y_i)\in \mathbf{D}_-^T\cup\mathbf{D}_+^C,\\
\langle \mathbf{w},\mathbf{x}_i\rangle + b_2 &\leq -1+\xi_{i,2}, \text{ for } (\mathbf{x}_i,y_i)\in \mathbf{D}_+^T\cup\mathbf{D}_-^C,\\
\langle \mathbf{w},\mathbf{x}_i\rangle + b_2 &\geq +1-\xi_{i,2}, \text{ for } (\mathbf{x}_i,y_i)\in \mathbf{D}_-^T\cup\mathbf{D}_+^C,\\
\xi_{i,j} &\geq 0, \text{ dla } i=1,\ldots,n,\ j\in\{1,2\},
\end{aligned}$$

Optimization task – primal form

We have two penalty parameters:

- C_1 penalty coefficient for being on the wrong side of one hyperplane
- C_2 coefficient of additional penalty for crossing also the second hyperplane

- All points classified as neutral are penalized with $C_1\xi$
- All definitely misclassified points are penalized with $C_1\xi$ and $C_2\xi$

How do C_1 and C_2 influence the model?

Influence of penalty coefficients C_1 and C_2 on the model

Lemma

For a well defined model $C_2 \geq C_1$. Otherwise the order of the hyperplanes would be reversed.

Lemma

If $C_2 = C_1$ then no points are classified as neutral.

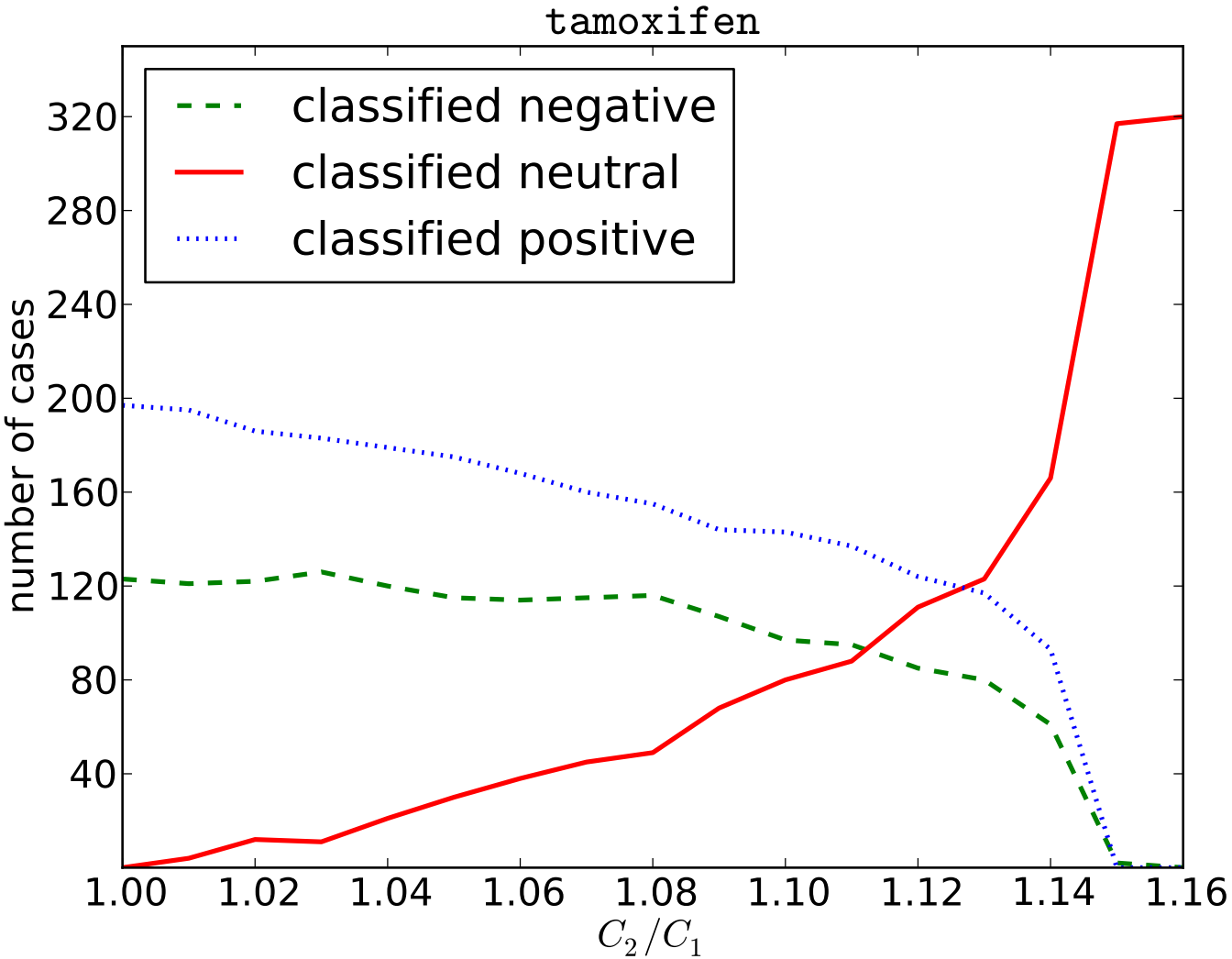
Lemma

For sufficiently large ratio C_2/C_1 no point is penalized for crossing both hyperplanes. (Almost all points are classified as neutral.)

Influence of penalty coefficients C_1 and C_2 on the model

- The C_1 coefficient plays the role of the penalty in classical SVMs
- The ratio C_2/C_1 decides on the proportion of cases classified as neutral

Example: the tamoxifen drug trial data



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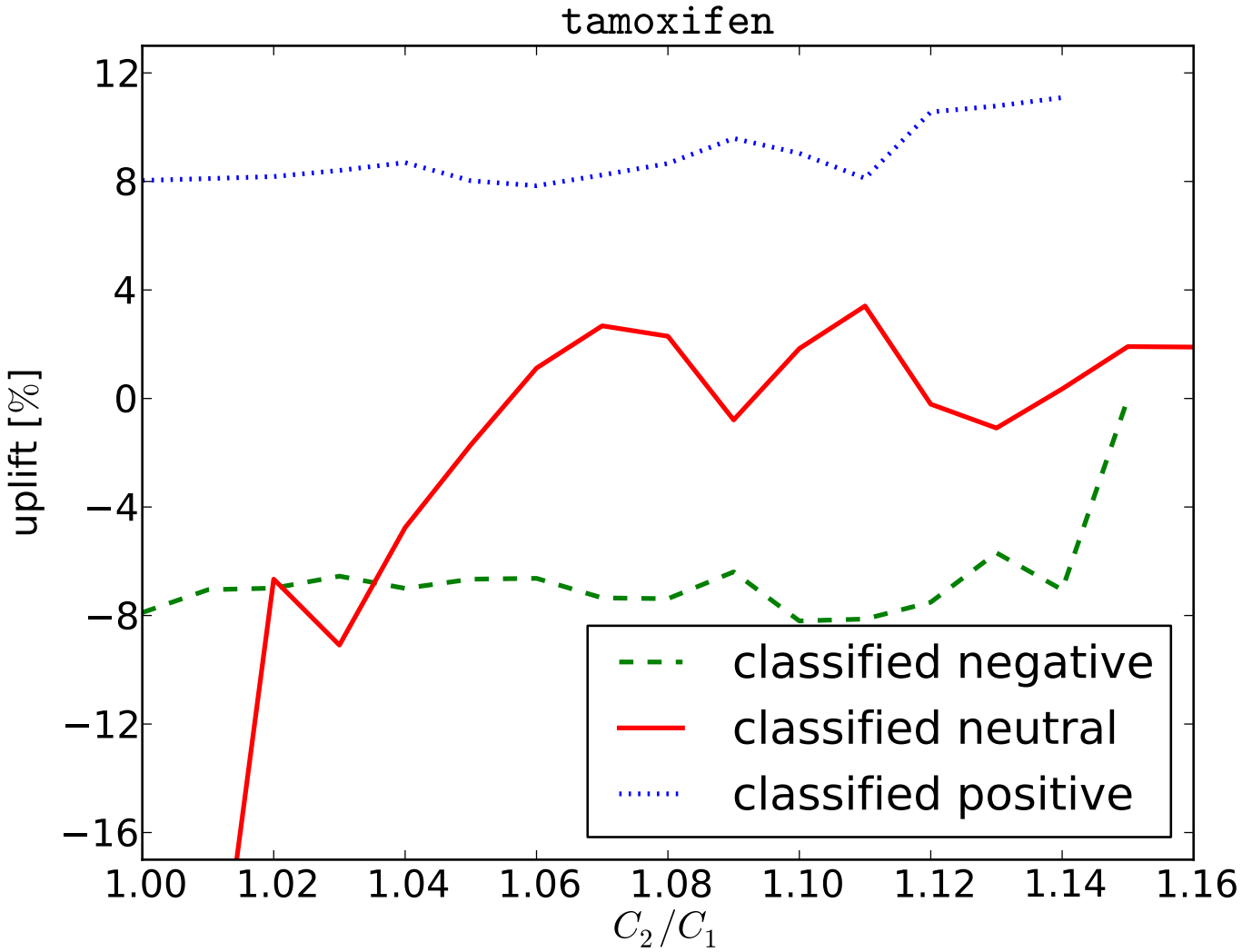


Evaluating uplift models

Evaluating uplift models

- We have two separate test sets:
  - a treatment test set
  - a control test set

Problem

To assess the gain for a customer we need to know both treatment and control responses, but only one of them is known

Solution

Assess gains for groups of customers

Evaluating uplift classifiers

For example:

Gain for the 10% highest scoring customers =

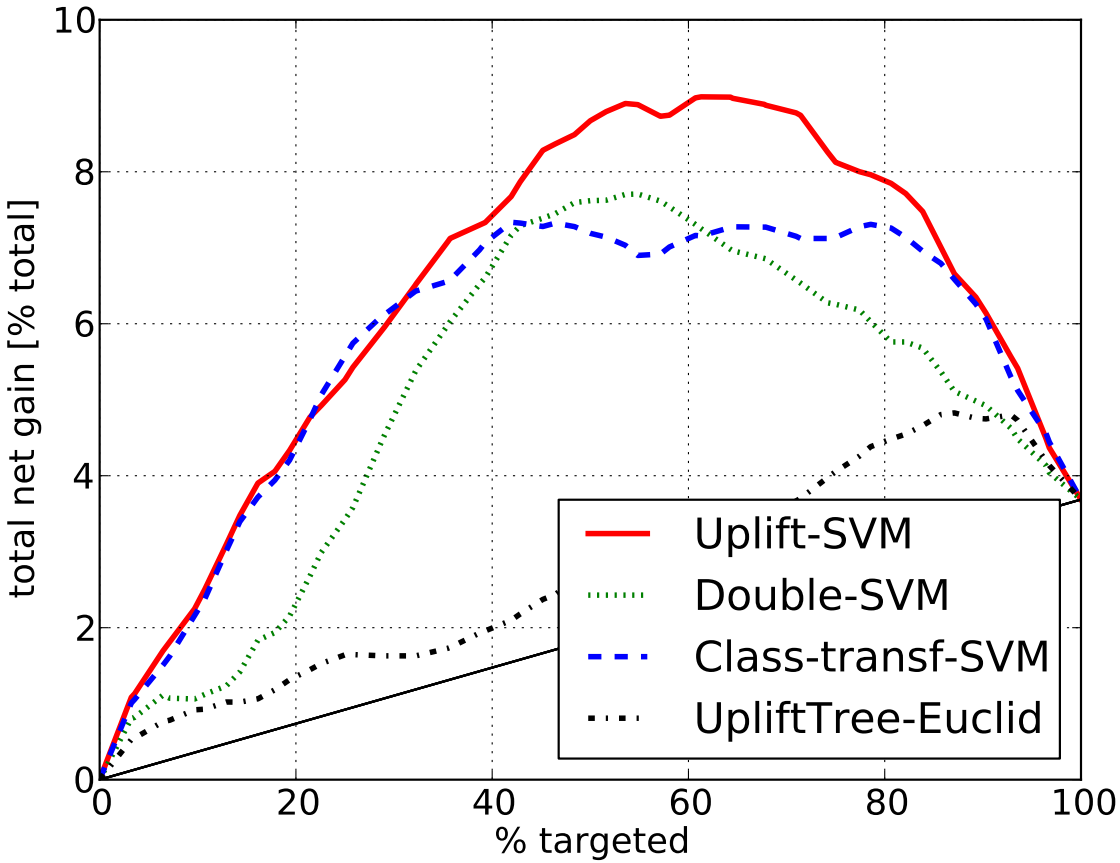
% of successes for top 10% treated customers

– % of successes for top 10% control customers

Uplift curves

- Uplift curves are a more convenient tool:
  - Draw separate lift curves on treatment and control data (TPR on the Y axis is replaced with percentage of successes in the whole population)
  - Uplift curve =
    lift curve on treatment data – lift curve on control data
  - Interpretation: net gain in success rate if a given percentage of the population is treated
- We can of course compute the Area Under the Uplift Curve (AUUC)

An uplift curve for UCI breast cancer data (artificially split into T/C groups)



Experimental evaluation

- Used 5 datasets with real control groups
- Used additional 13 dataset artificially split into T/C groups

- Uplift SVMs compared favorably with other models
  - better than double SVM model on 13 out of 18 datasets
  - better than uplift decision trees on 12 out of 18 datasets

Thank you!