

Uplift Modeling with ROC: An SRL Case Study

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The Task

What are we trying to accomplish?

- ▶ Identify patients with breast cancer who may be good candidates for watchful waiting.
- ▶ Use ILP to take advantage of our relational dataset and produce interpretable classifiers.
- ▶ Use metrics that are understandable to medical experts.

Breast Cancer Stages

There are two main stages of breast cancer.

In Situ

- ▶ Earlier stage
- ▶ Cancer is localized



Invasive

- ▶ Later stage
- ▶ Cancer has invaded surrounding tissue



Breast Cancer Age Differences

Breast cancer differs between older and younger patients.

Older

- ▶ Cancer tends to progress *less* aggressively
- ▶ Patient has *less* time remaining for progression

Younger

- ▶ Cancer tends to progress *more* aggressively
- ▶ Patient has *more* time remaining for progression

Overtreatment Problem

Who is treated?

Everyone

Overtreatment Problem

Who is treated?

Everyone

*Can we reduce costly and risky overtreatment in older patients with
in situ cancer?*

That is the goal

Watchful Waiting

Who are our most viable candidates for watchful waiting?

- ▶ Older
- ▶ In situ
- ▶ Sufficiently different from that of younger patients

Our Dataset

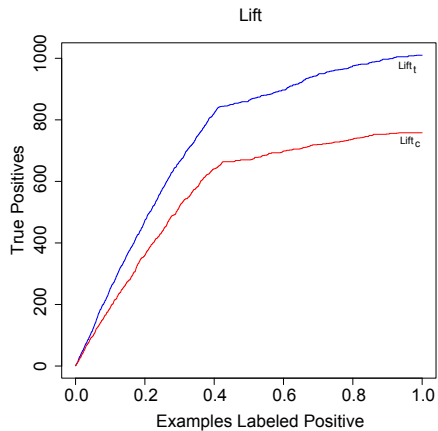
Older		Younger	
In Situ	Invasive	In Situ	Invasive
132	401	110	264

Uplift Modeling

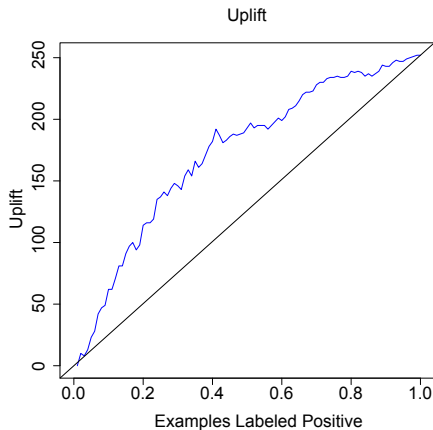
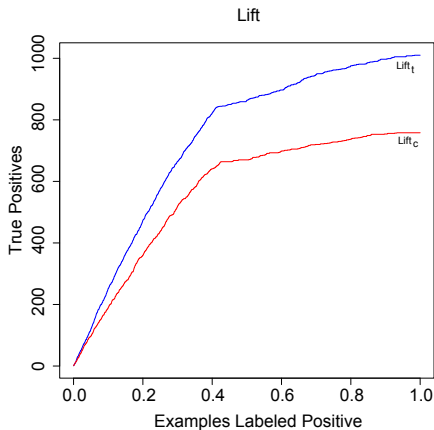
Uplift Modeling

Predictive modeling technique that attempts to specifically characterize a particular subgroup of a population.

Lift and Uplift



Lift and Uplift



$$Uplift = Lift_t - Lift_c$$

Understandable Metrics

What's the problem?

Lift isn't a common metric

Understandable Metrics

What's the problem?

Lift isn't a common metric

Can we achieve the same characterization using a different metric?

That is the goal

Differential ILP

How do we get an ILP algorithm to consider metrics like lift and ROC?

Start with Score as You Use (SAYU)

Differential ILP

How do we get an ILP algorithm to consider metrics like lift and ROC?

Start with Score as You Use (SAYU)

Now how do we make it differential?

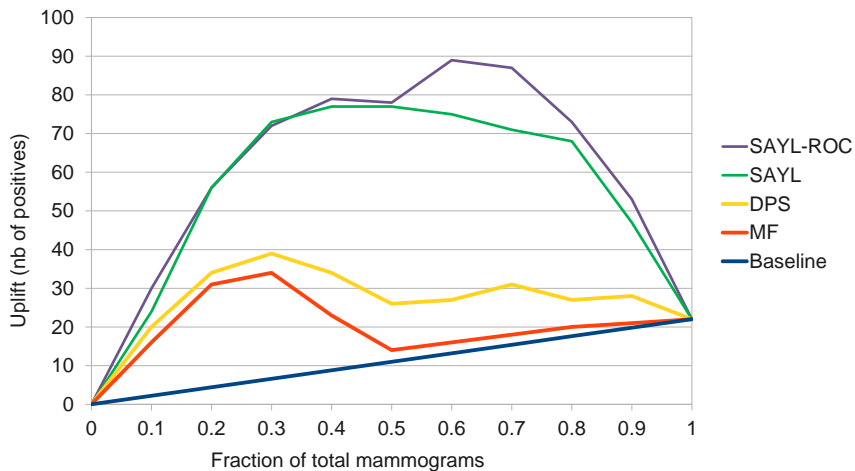
Train two classifiers instead of one

SAYL Algorithm

SAYL

```
Initialize naïve classifiers and theory
while Stop criteria not met do
  Select seed example
  Construct bottom clause
  while Clause space not exhausted do
    Select new clause
    Train classifiers with theory and new clause
    if New clause improves ROC difference then
      Add new clause to theory
      break
    end if
  end while
end while
```


SAYL-ROC Performance



Conclusions and Future Work

Conclusions

- ▶ No significant difference between SAYL and SAYL-ROC
- ▶ SAYL-ROC training may be easier to understand outside of marketing
- ▶ SAYL-ROC tends to construct much larger theories
- ▶ SAYL-ROC theories may be more difficult to interpret

Future Work

- ▶ Experiment with different class skews
- ▶ Experiment with different domains

Questions?

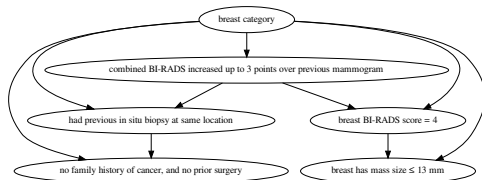
Learned Rules

Some example rules.

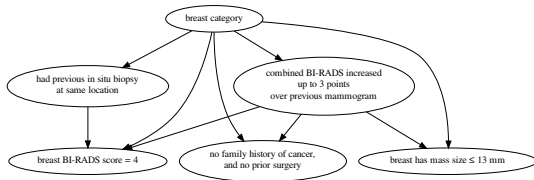
1. Patient had prior in situ biopsy,
BI-RADS score of prior biopsy was 1
2. Patient has low breast density,
principal finding is calcification or single dilated duct

SAYL TAN Models

TAN model learned on older population



TAN model learned on younger population



Marketing Customer Groups

Persuadables

Customers who will respond only when targeted.

Sure Things

Customers who will respond even when not targeted.

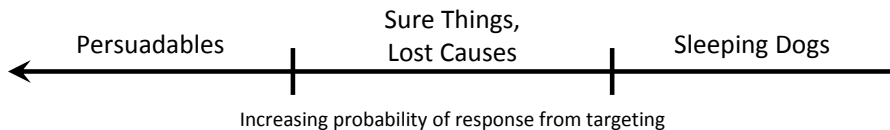
Lost Causes

Customers who will not respond, regardless of whether they were targeted or not.

Sleeping Dogs

Customers who will not respond as a result of being targeted.

Marketing Ideal Ranking



Marketing Dataset

Target		Control	
Response	No Response	Response	No Response
Persuadables Sure Things	Sleeping Dogs Lost Causes	Sleeping Dogs Sure Things	Persuadables Lost Causes

In Situ vs. Invasive Dataset

Older		Younger	
In Situ	Invasive	In Situ	Invasive
Indolent In Situ Aggressive In Situ	Always Excise	Aggressive In Situ	Always Excise