A Probabilistic Approach to the Positive and Unlabeled Learning Problem

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Traditional binary classification requires well-labeled data.

- Both positive and negative labels:

```
  y=1
  y=0
```

Negative data is EXPENSIVE in many interesting problems.

- Ex: Cancer Detection
  - Known positive set: People who have cancer
  - Unlabeled set: Everyone else
  - Finding true negatives – people who ABSOLUTELY do not have cancer – is expensive or impossible.

- This leaves us with some positive and no negative labels.

- Other examples:
  - Fraud detection
  - Terrorist detection
  - Threat detection

```
          True
Positives          Goal          True
  Positives
          True
Negatives
```

SCAR ASSUMPTION

- We assume that labeled positives are “Selected Completely At Random” from the set of all positive samples.
- Means labeled and unlabeled sets are completely non-separable.
- Means that there is a constant probability $c$ that a positive sample is labeled.

GOAL

- Given data samples $x$ and data labels $y$
- We want to learn a probabilistic classifier $p(y = 1|x)$

PREVIOUS SOLUTION [1]

- Include a new random variable $s$:
  - If sample is labelled, $s = 1$, if unlabelled, $s = 0$
- It can be shown that
  $$p(y = 1|x) = \frac{p(s = 1|x)}{c}$$
- Used Standard Logistic Regression (SLR) to learn non-traditional classifier $p(s = 1|x)$
- Constructed estimators for $c$ using a validation data. Found to be INEFFECTIVE in practice.

OUR SOLUTION

- Created a Modified Logistic Regression (MLR) to learn non-traditional classifier $p(s = 1|x)$
- Introduced learned variable $b$ into SLR equation:

$$MLR = \frac{1}{1 + b^2 + e^{-w^T x}}$$

MOTIVATION

RESULTS

- We compared SLR estimators in [1] with estimators using our MLR over different data sets.
- Metric: mean accuracy of $c$ value estimate.

<table>
<thead>
<tr>
<th>Data Separability</th>
<th>MLR</th>
<th>SLR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Well Separated Data</td>
<td>98.32%</td>
<td>86.53%</td>
</tr>
<tr>
<td>Mostly Separable Data</td>
<td>95.38%</td>
<td>65.78%</td>
</tr>
<tr>
<td>Poorly Separable Data</td>
<td>90.58%</td>
<td>43.51%</td>
</tr>
</tbody>
</table>

SECURITY APPLICATION USING SENSORS

- Threat detection on military bases or public venues

Given sensor input such as audio, video, satellite

- Known positive set: Previous attacks
- Unlabeled set: Everything else

Just because an attack didn’t occur, doesn’t mean that a threat wasn’t present – perhaps the attack was cancelled at the last minute.

REFERENCES


Sensor Signal and Information Processing Center
https://sensip.asu.edu