8/5/2015

DETC2015- 47401

A Computer Vision Approach for Automatically Mining and Classifying End of Life Products and Components

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Outline

- Introduction
- Motivation
- Methodology
- Case Study
- Conclusions

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End of Life Products

- Recovery and disposal of products at the end of their life is an integral part of the product lifecycle
- These products and components can be sourced for parts and raw materials
- Generates billions of dollars, over 1 million people employed (EPA)

State of the Art

Design	Planning	Recycling/Remanufacture	Sorting
Favi et al. (2012)	Behdad et al. (2010,2012)	Johnson & Wang (2010)	Zikopoulos & Tagaras (2008)
Huang et al. (2010)	Kang et al. (2014)	Zhao & Thurston (2013)	Oguchi et al. (2011)
Gonzalez-Torre (2004)	Kwak et al. (2011)	Kwak & Kim (2014)	Hatayama et al. (2012)
Peng et al. (2013)		Rahman & Subramanian (2012)	Gaustad et al. (2012)

Knowledge Gap

- Extant literature incorporates sorting into costs
- Labor accounts for 60% of EOL costs[1]
- Can easily become unprofitable

[1]: http://msl.mit.edu/theses/Dantec_D-thesis.pdf

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EOL Process

Source: http://www.call2recycle.ca/

Inefficiencies of Sorting

- End of Life recovery is a highly manual process
  - Identification
  - Sorting
- In some cases, tasks that can be done using computer vision

Steps to Sort

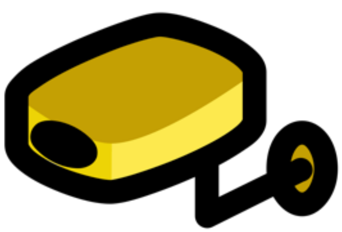
Current Practice

Observe

Identify

Classify

Observe



Identify

Classify

Research Hypothesis

Automatic classification of EOL objects provides comparable performance to that of a human sorter

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Methodology

Gather Waste Stream Video Data → EOL Object Recognition → EOL Object Classification → Real Time Enterprise level EOL Decision Making

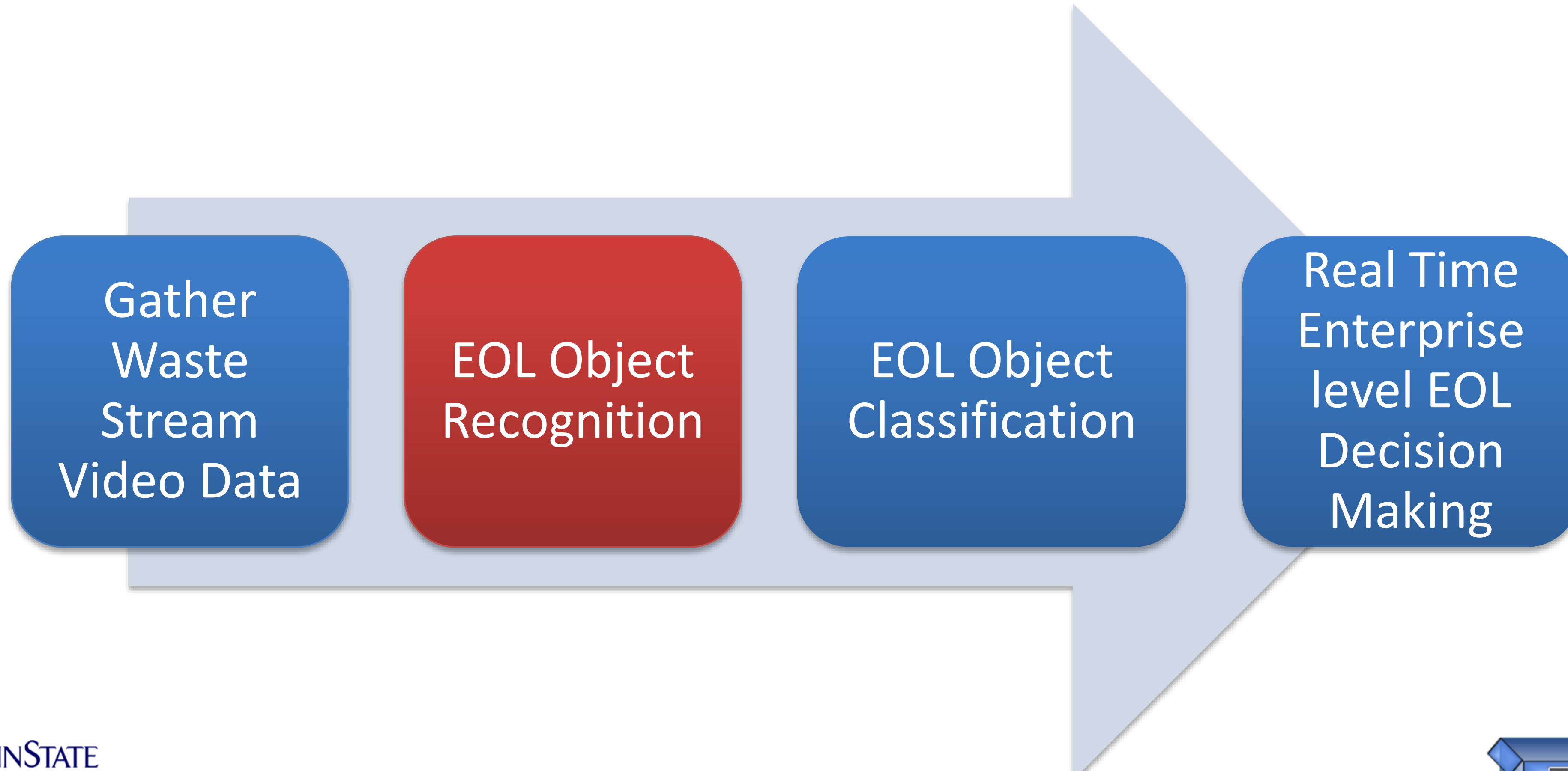
Gather Waste Stream Video

- Incoming data is any video containing EOL products already on-belt
- Each video can be represented as a series of matrices of color data

1

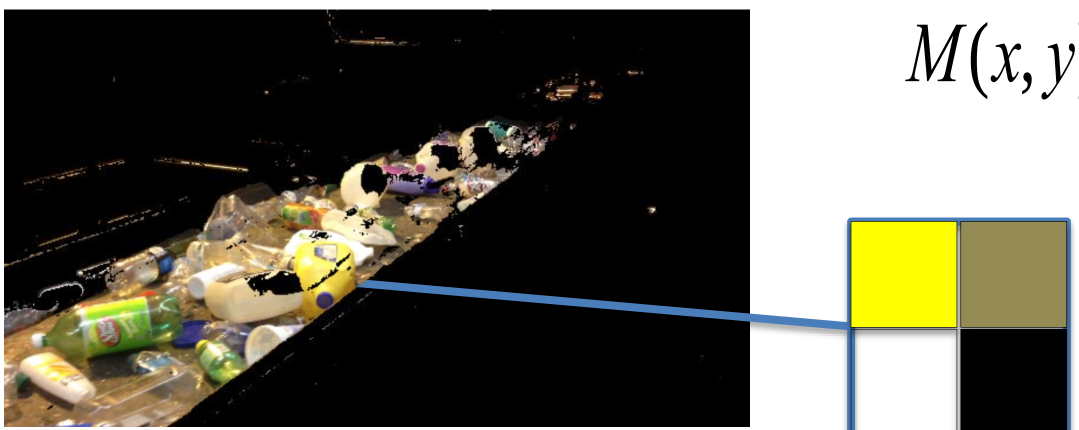
0 0 255	0 255 0	0 255 0
0 0 255	255 0 0	0 255 0
255 0 0	0 0 255	255 0 0

Methodology



EOL Object Recognition

- Key insight: EOL objects are moving
- By removing non-dynamic pixels, only potential EOL objects remain.



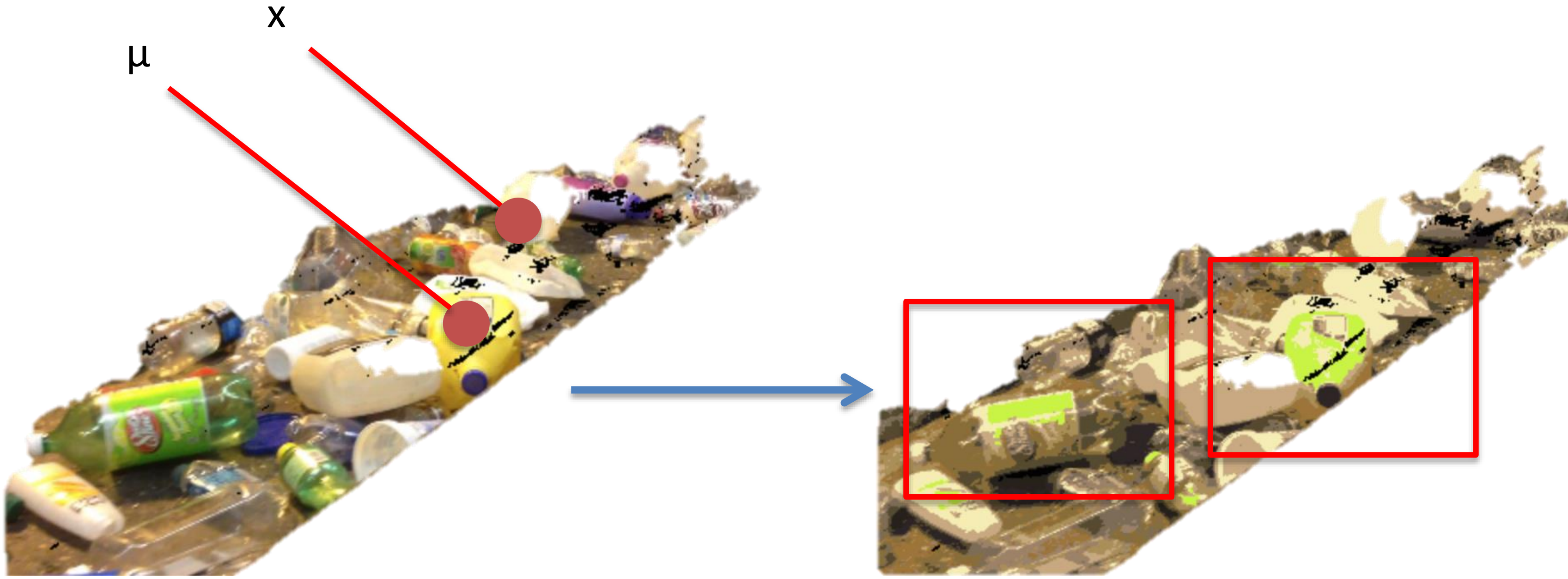
$$M(x,y) = \begin{cases} 1 & I(x,y)_{t-1} - I(x,y)_t \geq \varepsilon \\ 0 & I(x,y)_{t-1} - I(x,y)_t < \varepsilon \end{cases}$$

M = Mask
I(x,y) = Intensity of (x,y)
ε = threshold

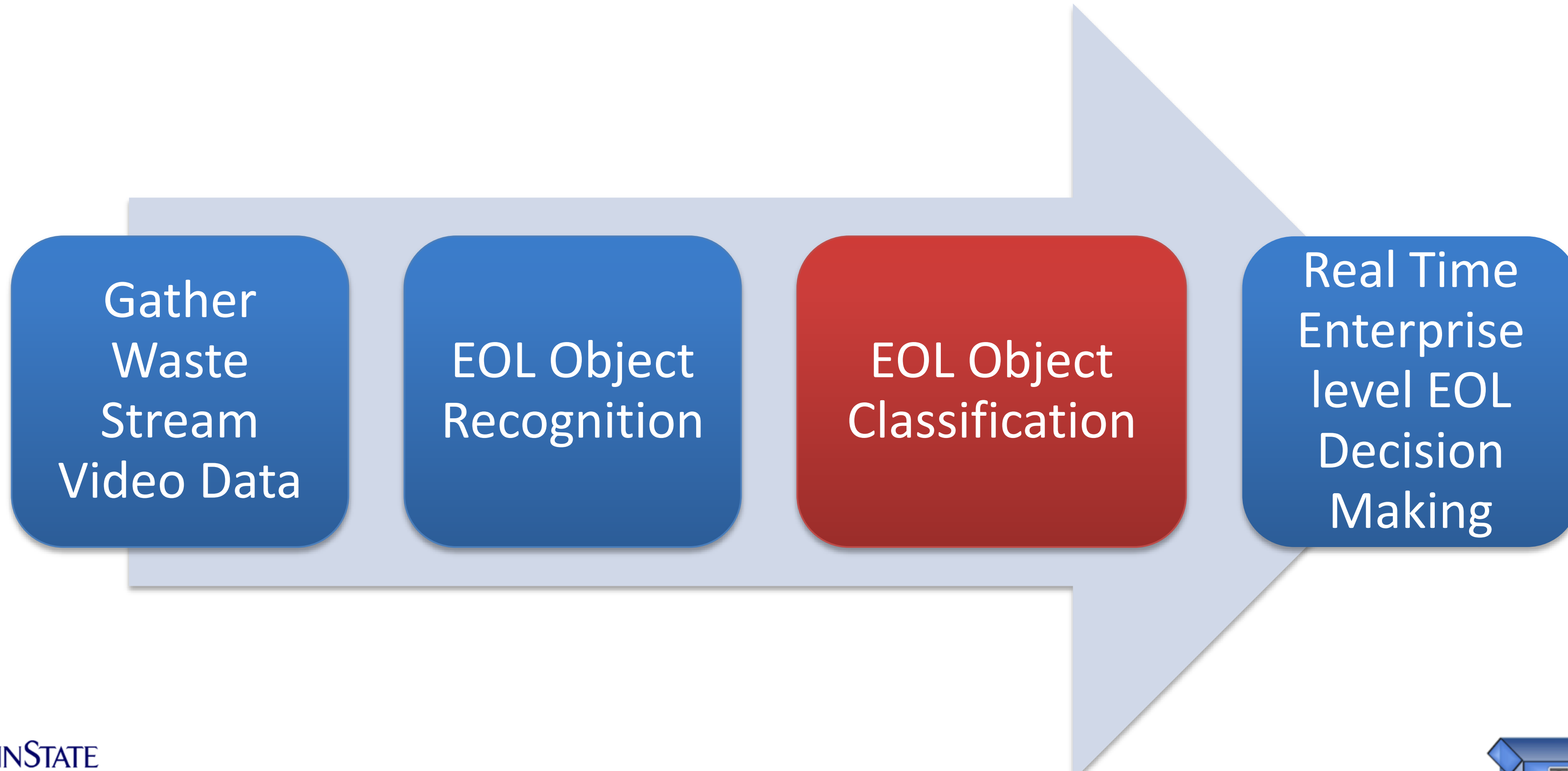
Identify Regions of Interest

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|^2$$

- Convert to LAB Space
- K-means

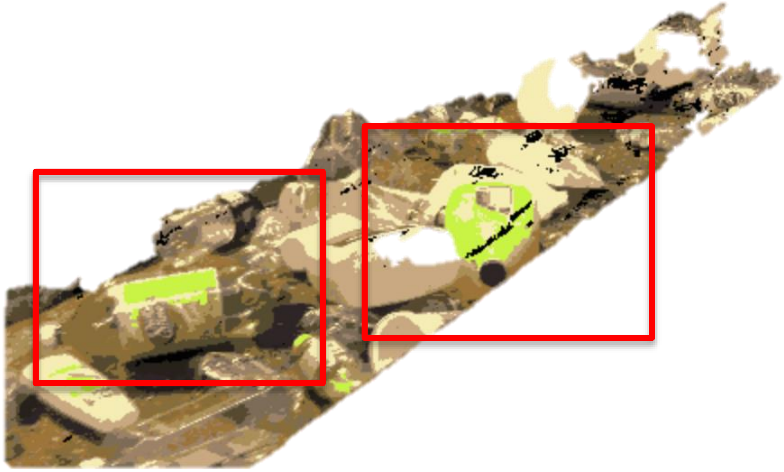


Methodology



Object Classification

Candidate Objects



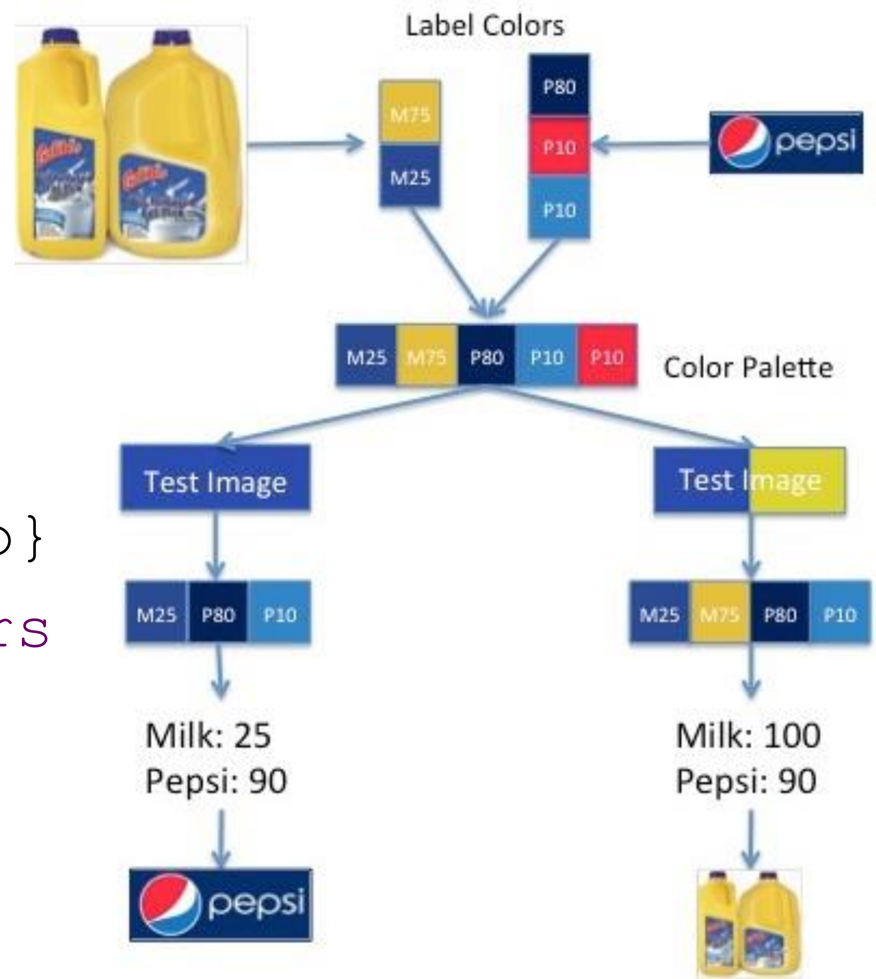
Ground Truth

Object Classification

- Each object being searched for is also quantized into a color palette
- These palettes are merged into a search space

Object Classification

```
space := {EOL objects}
For each i in space do
  quantize i
  save to palette
Merge similar colors
colors := {Quantize video}
For each color j in colors
  if j in palette
    assign label
```



Input Video Processing

- Apply moving pixels mask
- Cluster remaining colors
  - Key idea is to find large continuous areas
- If there is a color match, assign a label
- Aggregate label results

Methodology

Gather Waste Stream Video Data → EOL Object Recognition → EOL Object Classification → Real Time Enterprise level EOL Decision Making

EOL Enterprise Decision Making

Maximize π:

$$\pi = \left\{ \sum_{d \in D} \sum_{r \in R} a_{dr} \cdot \left(P_{dr} - C_{dr}\right) \right\}$$

P_{dr} = Revenue of decision d for product r
a_{dr} = number of units of product r and decision d
Cdr = Cost of decision d for product r

We need to find *a* for each *d,r*

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Case Study: Centre County Recycling

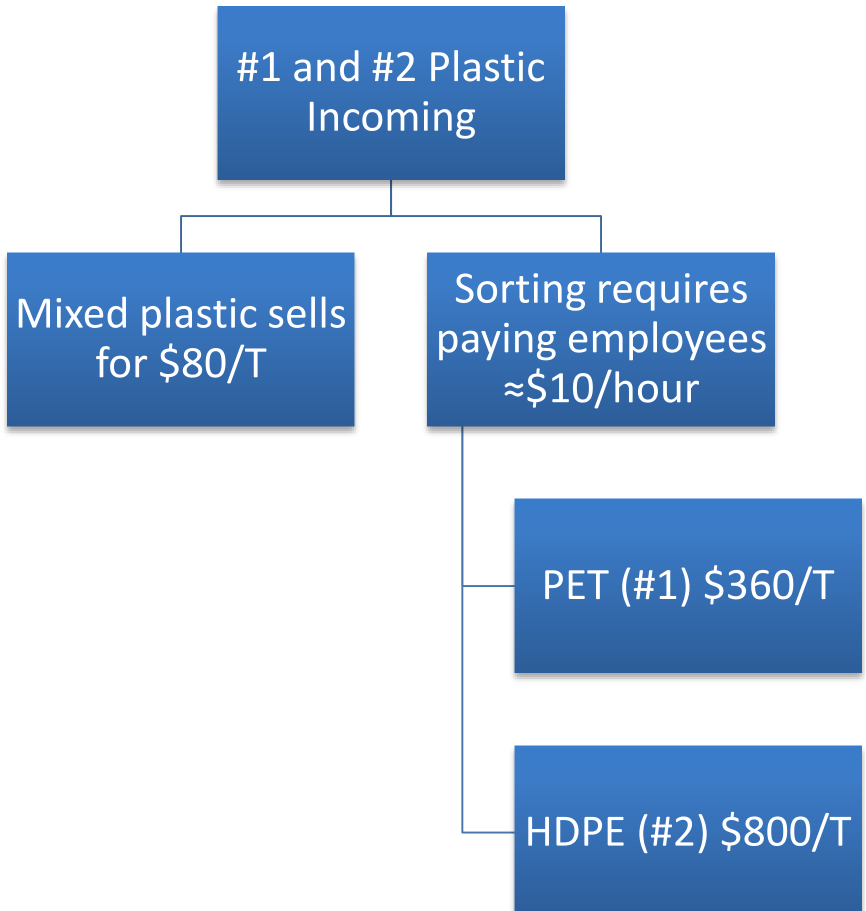
- Our Case Study is a local Recycling Center
- Processes approximate 200 lbs of plastic per *hour*

Case Study

- Decision to be made: Whether or not to sort a given load of plastics

	Decision		
Operation	Discard	Sort	Do Not Sort
Collection	X	X	X
Transport to Disposal Site	X		
Sorting *		X	
Trans to Market		X	X
Trans to Disposal Facility	X		

Why Sort?


#1 and #2 Plastic Incoming
Mixed plastic sells for $80/T
Sorting requires paying employees ≈$10/hour
PET (#1) $360/T
HDPE (#2) $800/T

Case Study

- Real-time Decision Making
  - Monitor video feed
  - Based on identified objects, determine if it is more profitable to sort

Results

Video	Precision	Recall
1	50%	71%
2	78%	84%

Profitability

- Based on 3:12 video:
  - 49 HDPE objects found
    - 8 missed
- Using this system to sort instead of humans:
  - +$10/Hr in unpaid wages
  - -$6.17/Hr in losses due to misidentification
- +$3.83/Hr in profits * 4160 Hrs = $16,000

Conclusion

- By using object identification, real time decisions can be made for objects on a conveyor belt
- Can greatly reduce labor costs, even in light of less than perfect recall

Future Work

- Improve Algorithm Generalizability
- Consider other EOL decisions

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Questions?

Thank you!