

Deep Context for Fine-Grained Object Recognition in Crowded Images

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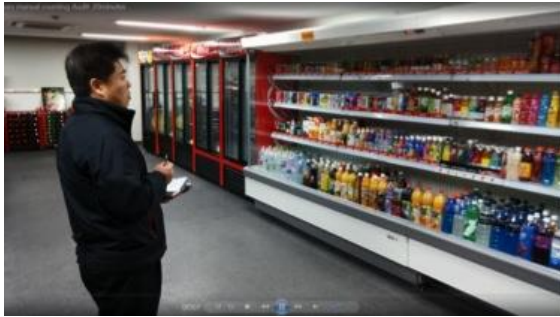
AGENDA

- Trax Visual Challenges
- Deep Context Embedding Architecture
- Implementation Details
- The Detection Challenge
- Summary



Trax's Business Application

Manual Audit



Trax Automatic Recognition Audit



Slow and Expensive
Inconsistent
untraceable



Fast and Cheap
Consistent
Traceable



'Big Data'
for retail



AVAILABILITY



SHARE OF
SHELF



PRICING



PROMOTIONAL
ACTIVATIONS



COMPETITIVE
INSIGHTS



PLANOGRAM
COMPLIANCE



SHELF
STANDARDS

Trax unlocks 'Big Data' for the retail industry

Scale of the Data

Market

Market share, trade channels, segments, competition

Retailer

Brand champions, generic brands, range review

Store

Product location, assortments, shelf share

Shelf

NPD, POSM, Pricing, Promotions

Scale of coverage



Welcome to Trax Universe



Trax's Visual Challenges



Classes

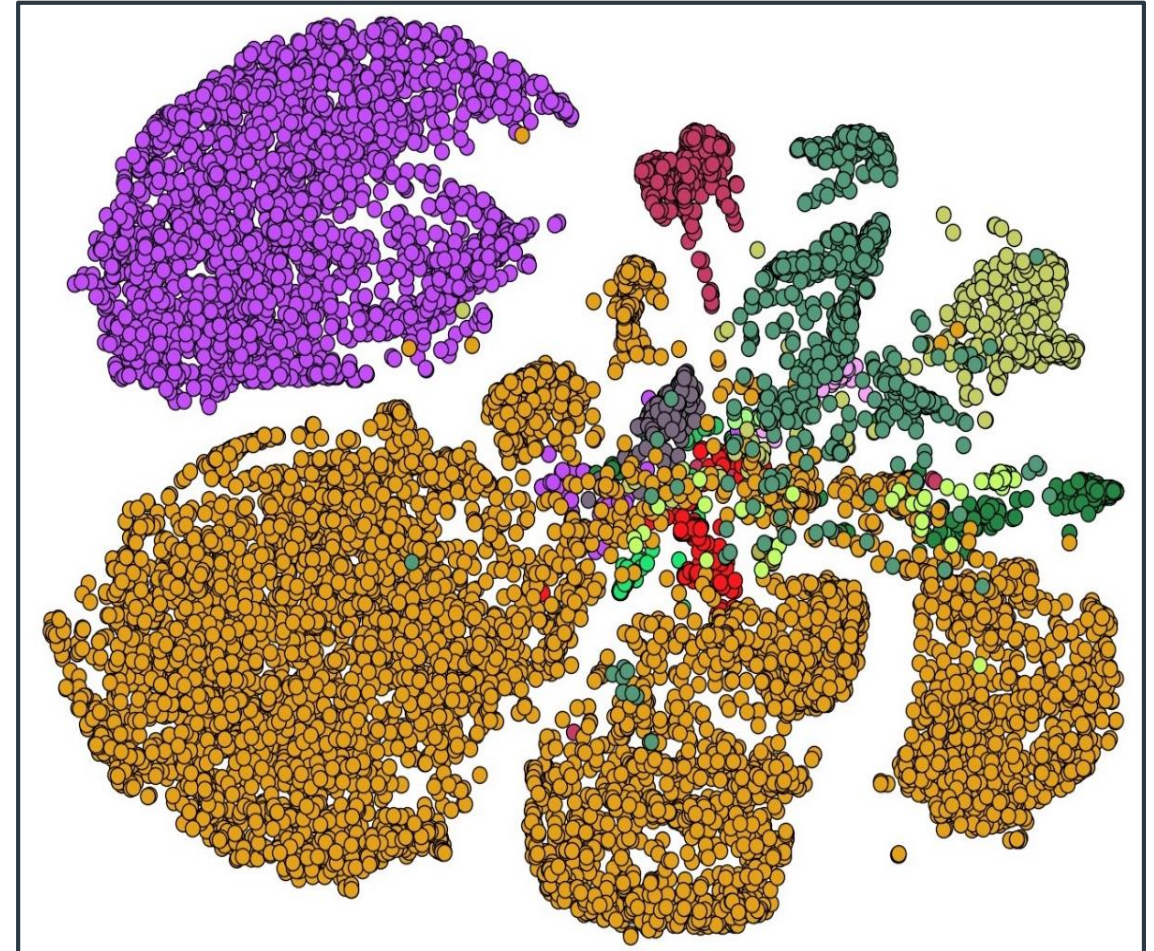
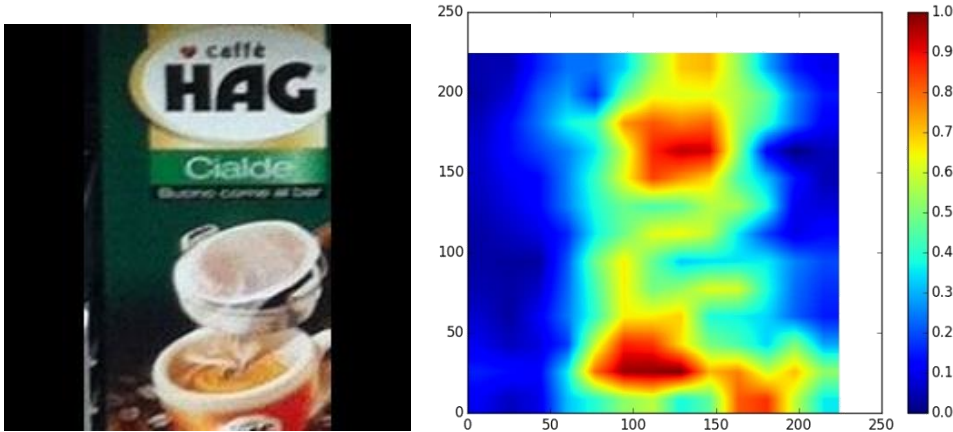
Fine-Grained Classification

Crowded Scene

Dynamic Dataset



Last Year- CNN: Opening The Black Box

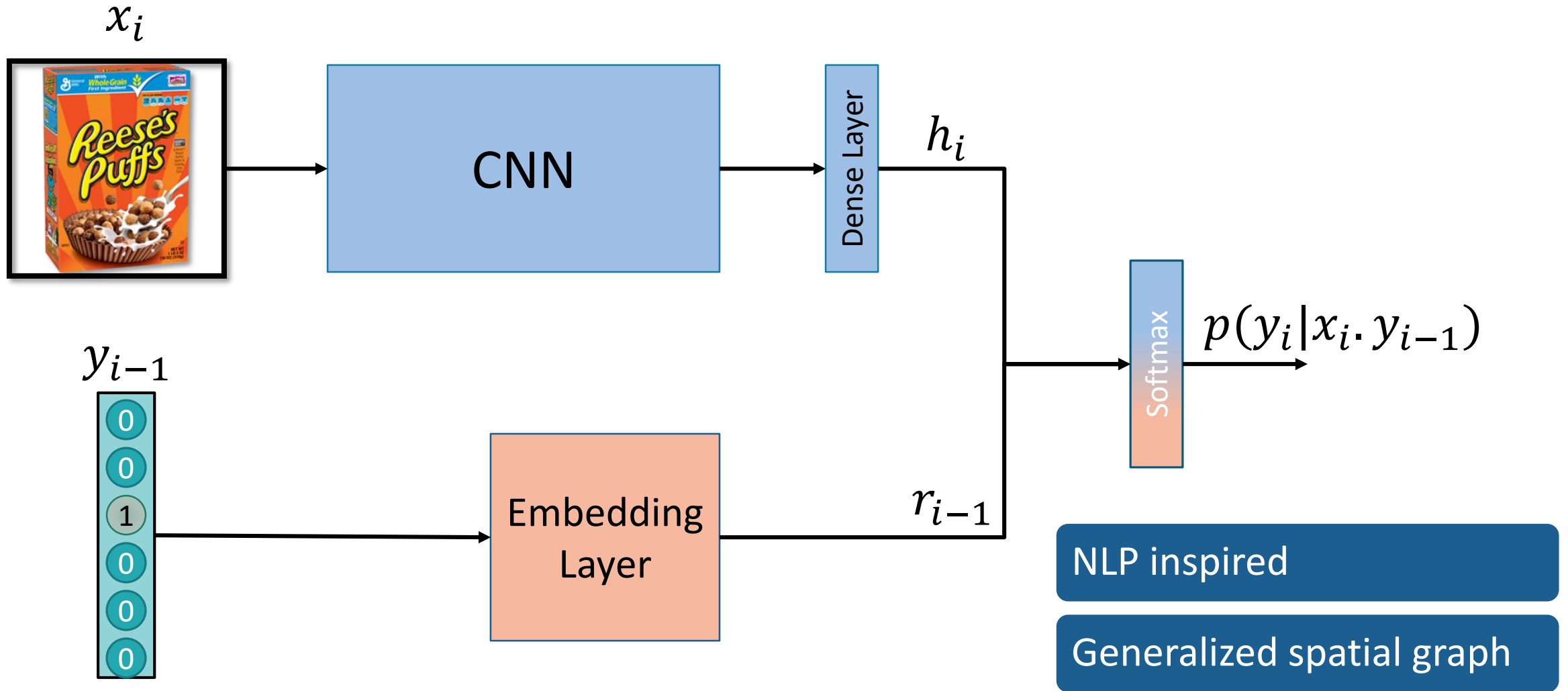


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New DNN architecture

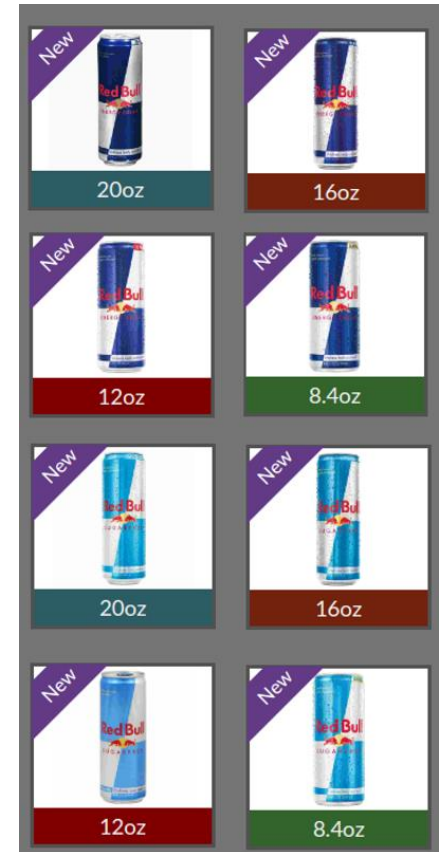


Which one is it?



Object

classes

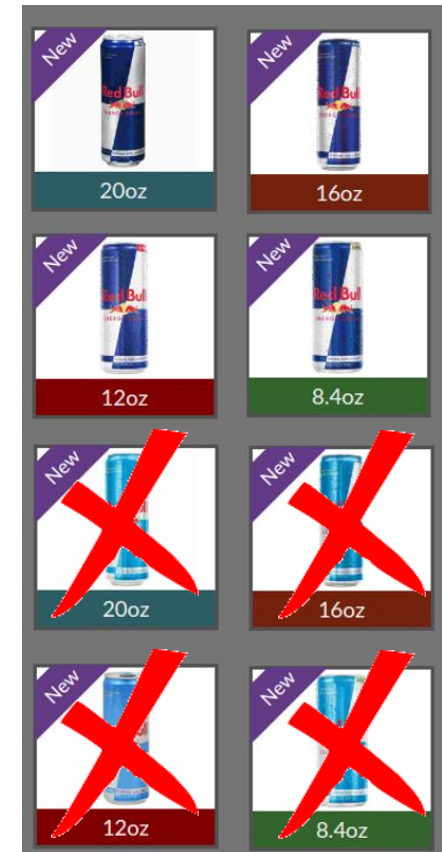


Which one is it?



Object

classes



Which one is it?



Object

classes



Which one is it?



Object

classes



Which one is it?

classes

Flavors with red labels:

Classic



Decaf



Lemon



Vanilla



Ginger



X Sizes:



0.35



0.47



0.5



0.6



1



1.25



2

Object



Which one is it?

Object

classes

Flavors with red labels:



Classic

Decaf

Lemon

Vanilla

Ginger



X Sizes:



0.35



0.47



0.5



0.6



1



1.25



2

Which one is it?

classes



0.35
ltr
(12 OZ)

0.47
ltr
(16 OZ)

0.5
ltr

0.6
ltr
(20 OZ)

1
ltr

1.25
ltr

2 ltr

Object



Which one is it?

classes



Object



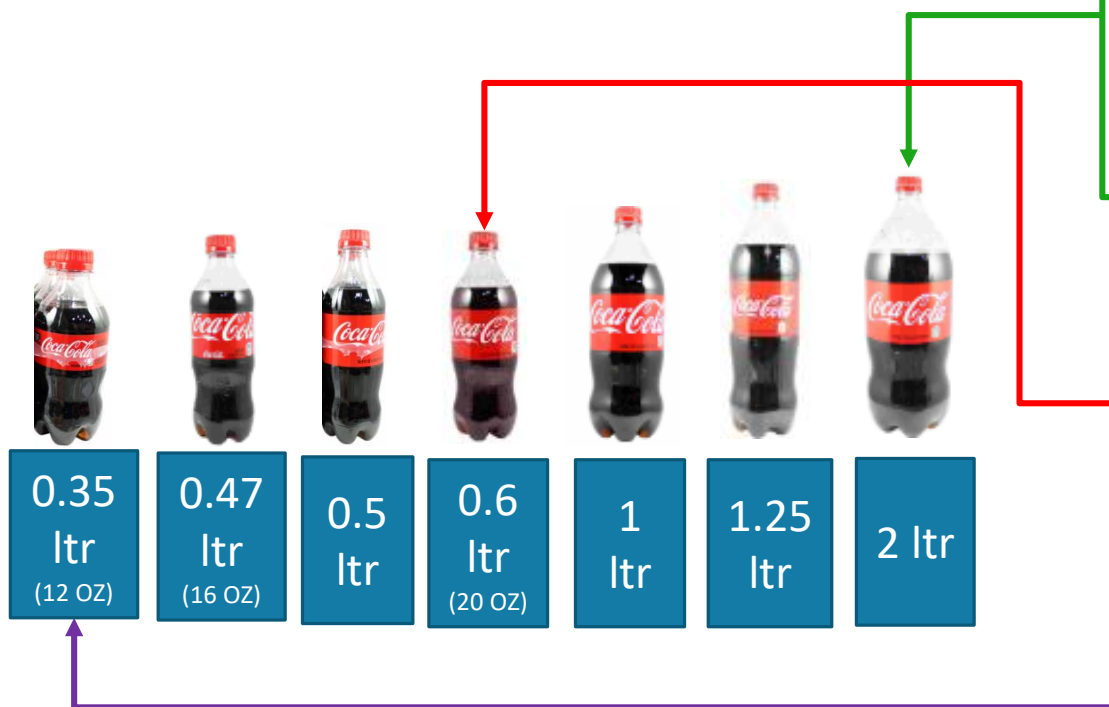
Which one is it?

classes



Object





Natural Language Processing Analogy

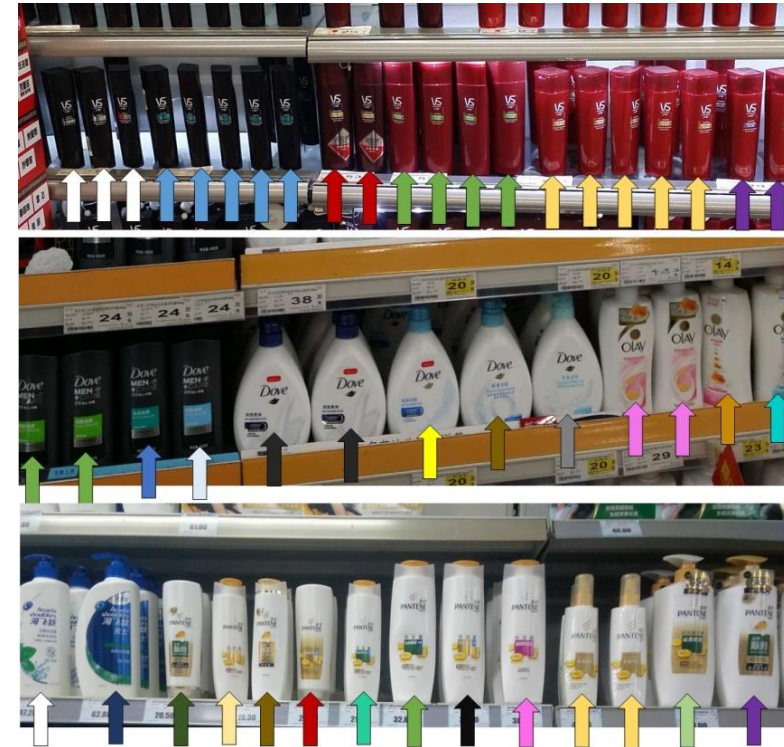
SENTENCES

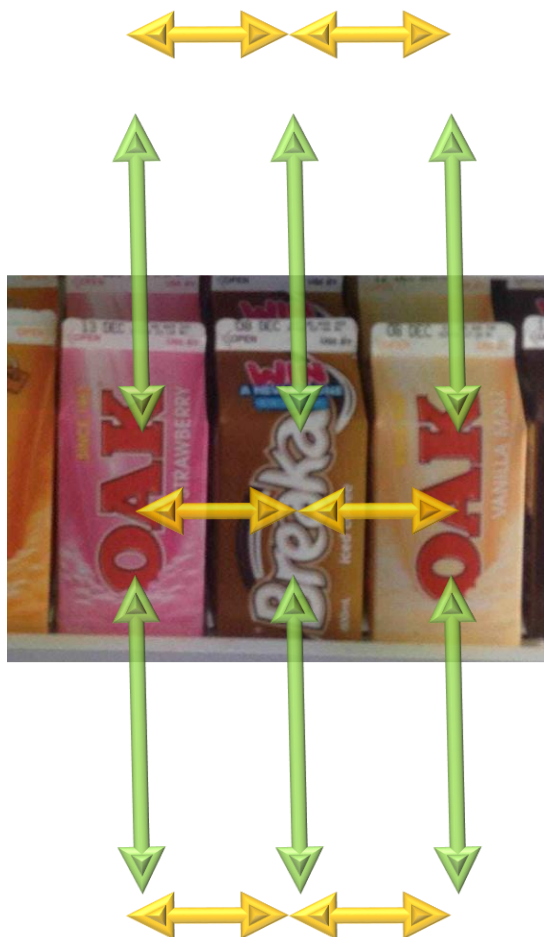
A tall glass of **orange juice** is the very image of refreshment.

Overwatering an **orange tree** can cause the leaves to turn pale.

The fiber content in an **orange peel** makes you feel fuller after eating.

SHELVES





Yes We Can

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Extended “Sentence”

Model image as a graph



Detection Node



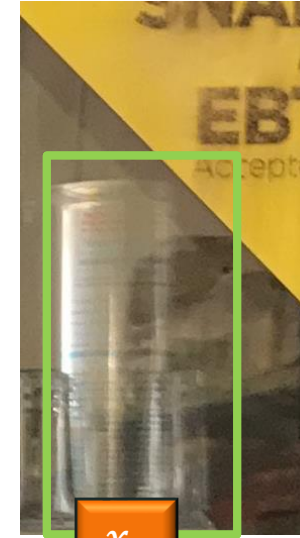
Left-Right Relation
Edge



Top-Bottom Relation
edge

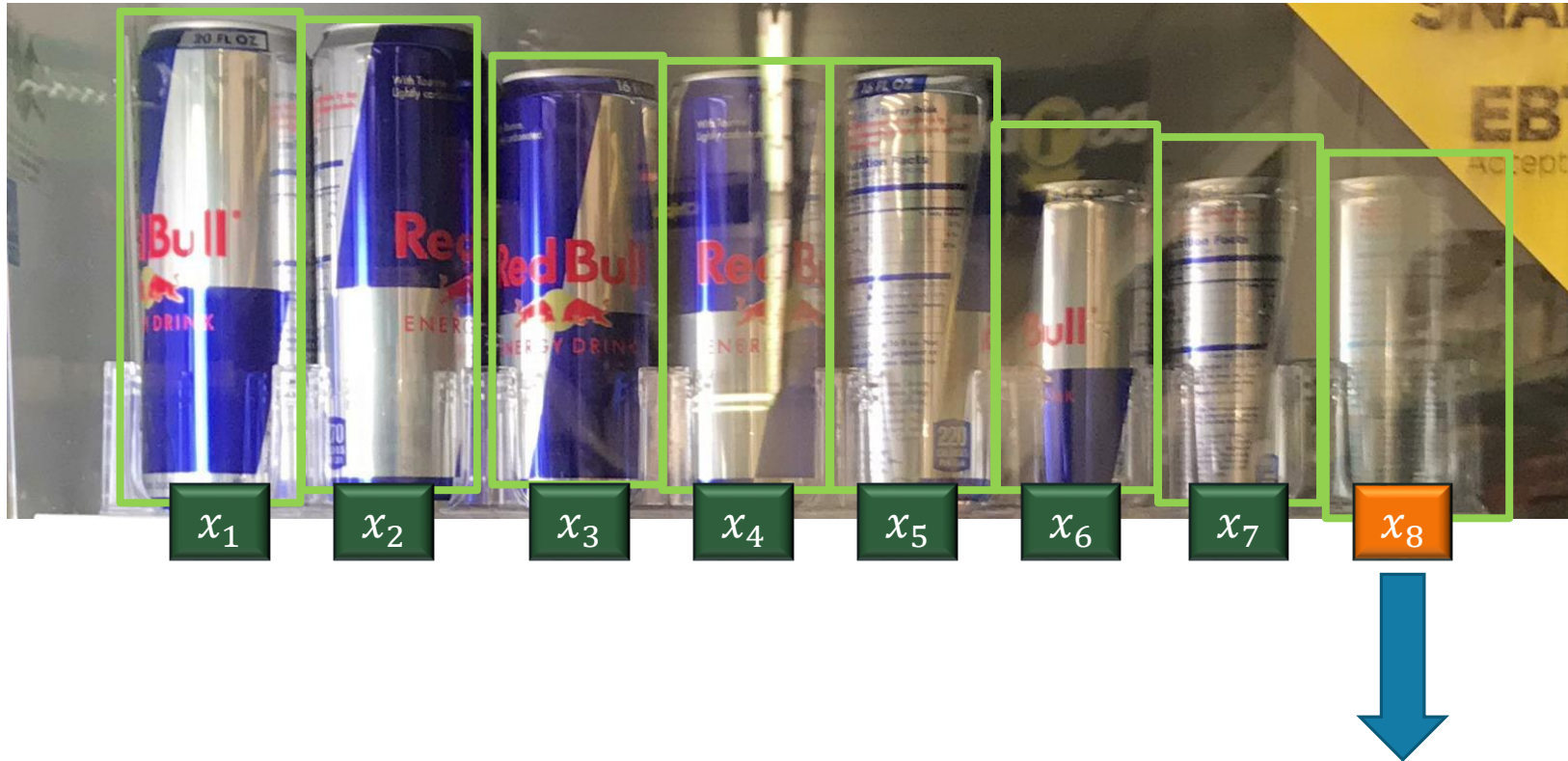


Classification

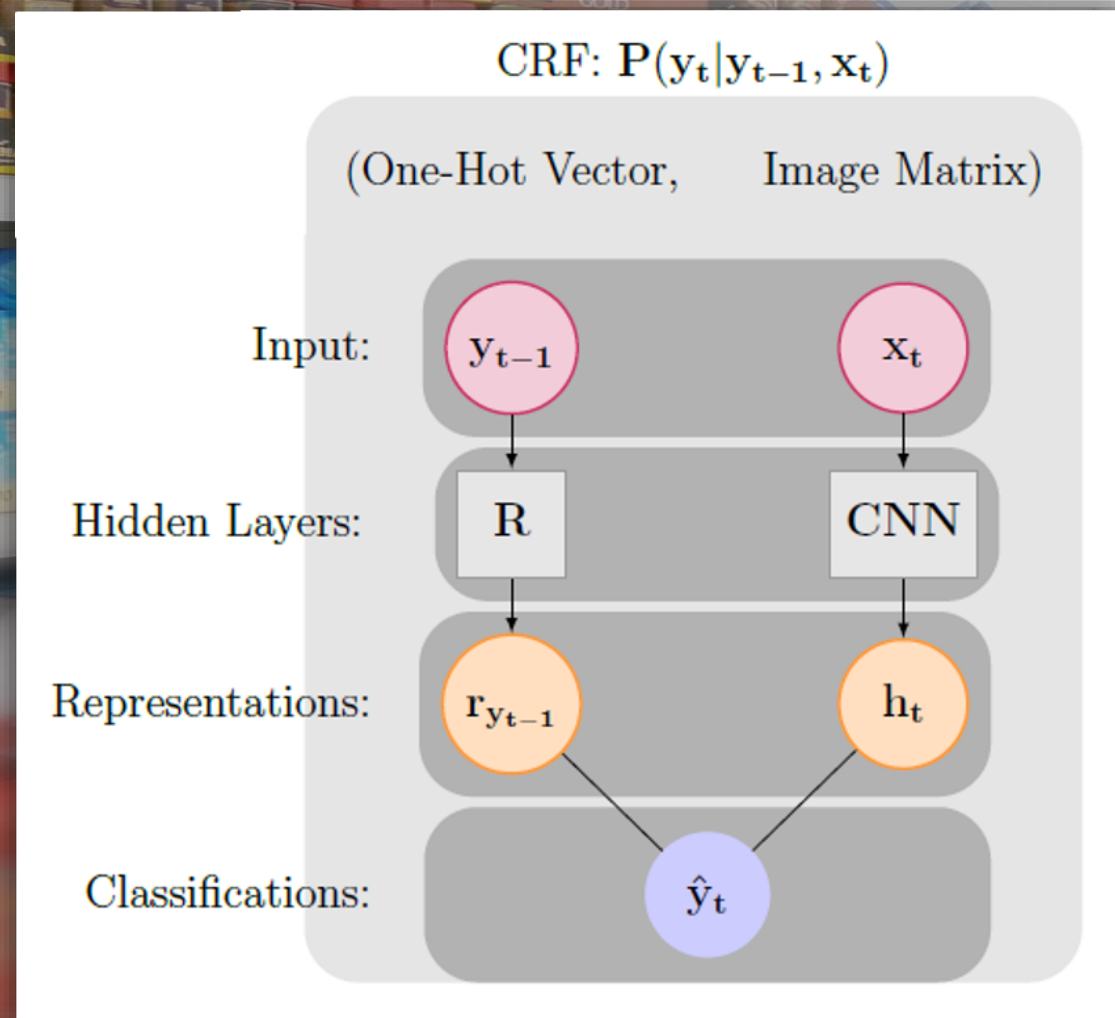


$$P(y_8|x_8)$$

Classification



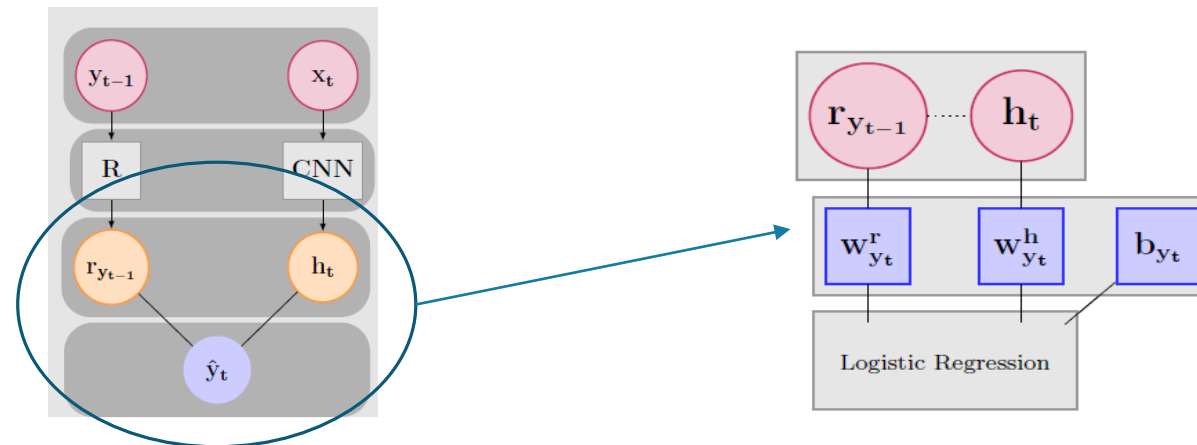
$$P(y_8 | x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8)$$



Joint Probability
Distribution



$$P(Y/X) \propto \prod_{t=1}^n \varphi(y_t | x_t, y_{t-1}) \propto \prod_{t=1}^n e^{[r_{y_{t-1}}^T, h_t^T] W_{y_t} + b_{y_t}}$$



Marginal
Distributions



$$P(y_t = i | X) = \sum_{Y/y_t} P(Y/X) =$$

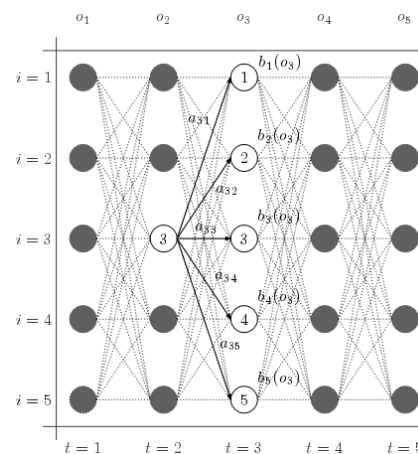
$$\sum_{Y/y_t} P(y_1, y_2, \dots, y_{t-1}, i, y_{t+1}, \dots, y_n | x_1, x_2, \dots, x_n) \propto$$

$$\sum_{Y/y_t} \prod_{\tau=1}^n e^{h_{\tau}^T u_{y_{\tau}} + b_{y_{\tau}}} e^{r_{y_{\tau-1}}^T q_{y_{\tau}}} = \alpha(y_t) \cdot \beta(y_t)$$

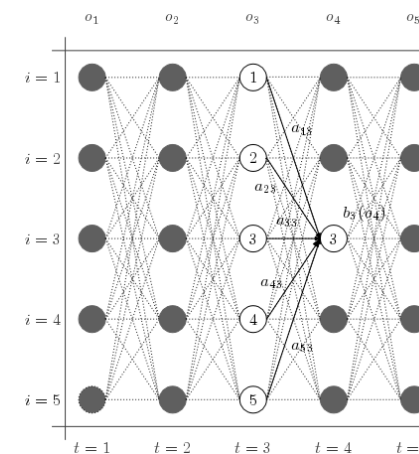


Dynamic programming:
Forward-backward algorithm

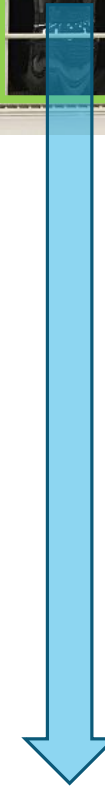
$$P(y_t|X) = \frac{1}{Z} \alpha(y_t) \beta(y_t)$$



$$\alpha(y_t)$$



$$\beta(y_t)$$



Classification:

$$P(y_i|x_i)$$

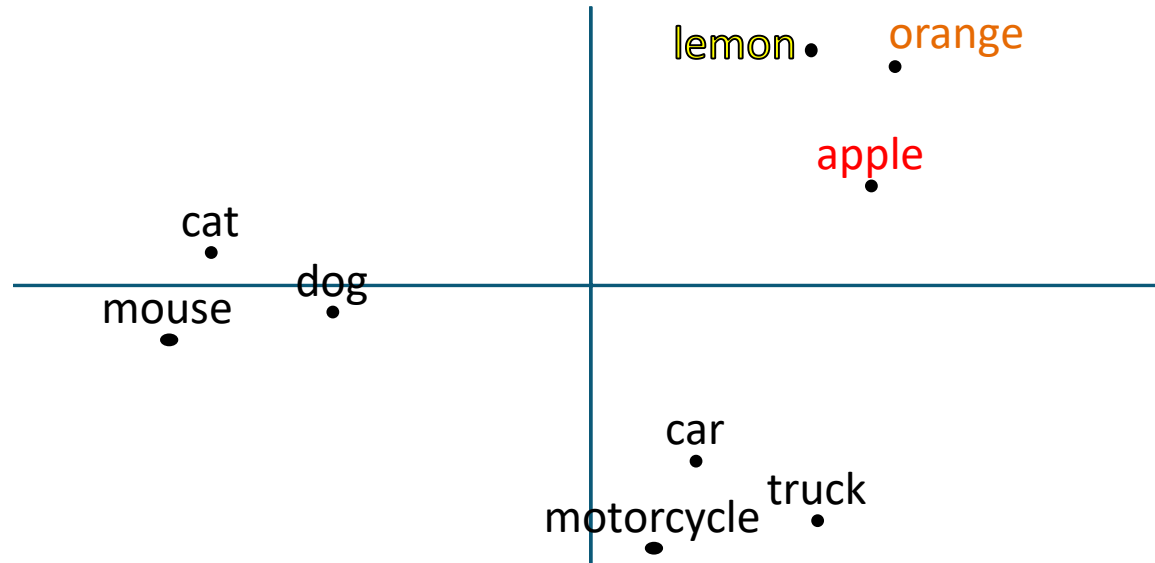
Spanning Tree Belief-Propagation



Classification: $P(y_i|X)$

Word Embedding 2nd Order Similarity

Orange juice	Lemon juice
Orange water	Lemon water
Orange tree	Lemon tree
Orange seed	Lemon seed
Orange peel	Lemon peel
Orange pulp	Lemon pulp
Orange orchard	Lemon orchard
Orange milkshake	Lemon milkshake
Orange pie	Lemon pie
Orange soda	Lemon soda
Orange plantation	Lemon plantation
Orange drink	Lemon drink
Orange flavored	Lemon flavored
Orange cider	Lemon cider
Orange vinegar	Lemon vinegar

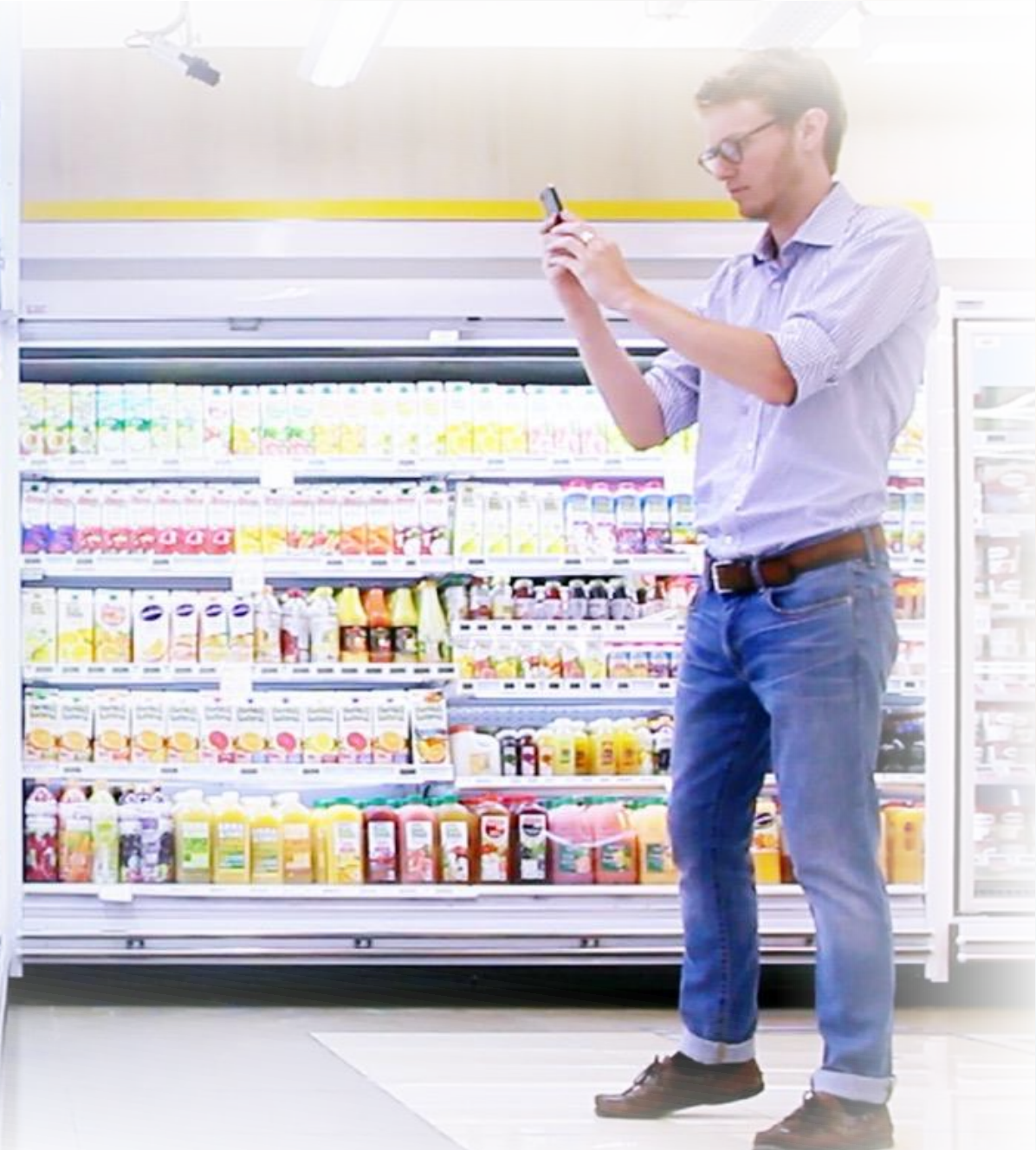


Product Embedding 2nd Order Similarity

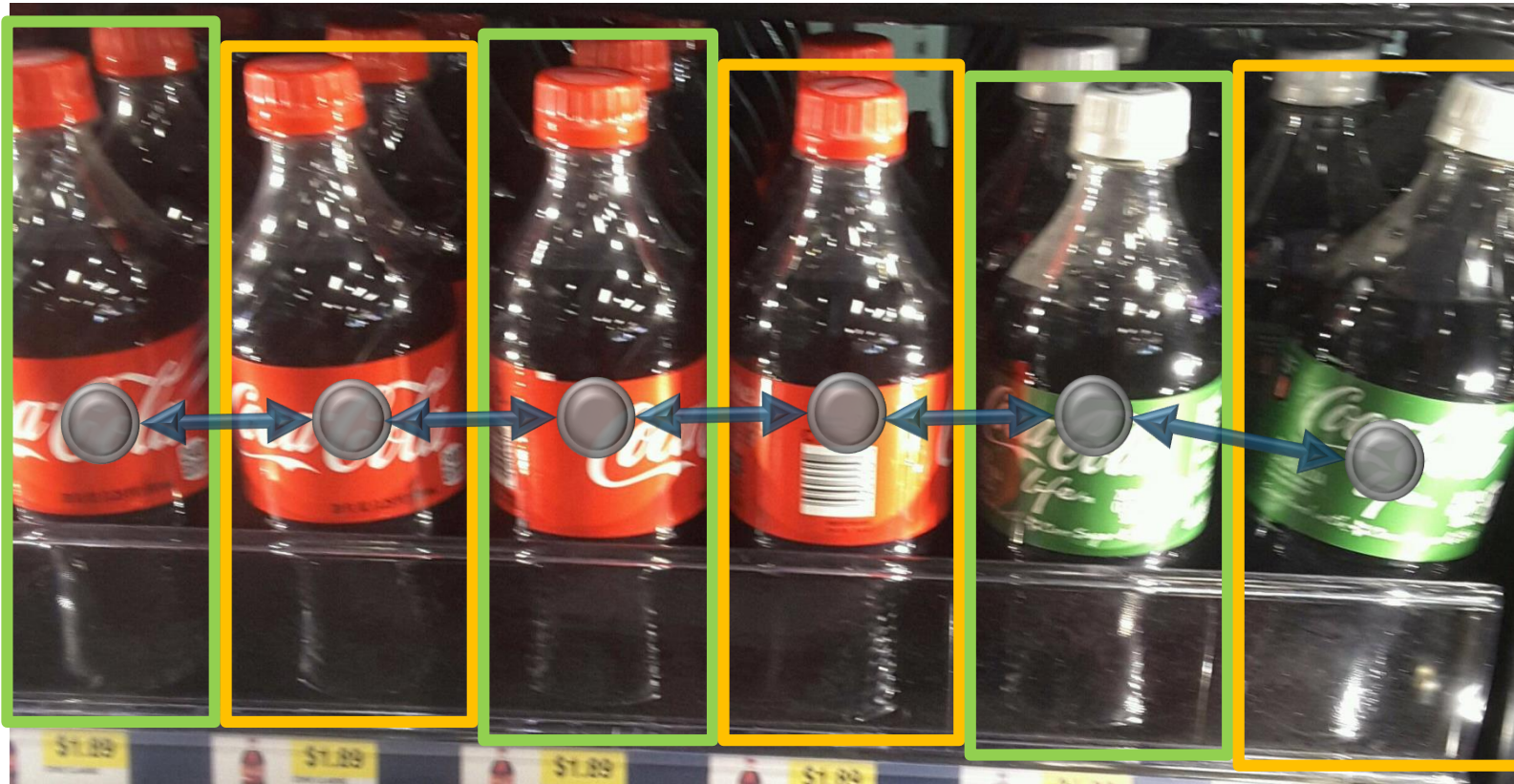


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Correct Detection



Missing an object

you shall ~~not~~ pass



Splitting an object

....the fireworks on the fourth of July



State of The Art Detectors

“YOLO imposes strong spatial constraints on bounding box predictions”

Redmon, Joseph, et al. "You only look once: Unified, real-time object detection."

“SSD is very sensitive to the bounding box size”

Liu, Wei, et al. "SSD: Single shot multibox detector."

“Trying to directly regress to constitutes a difficult learning task”

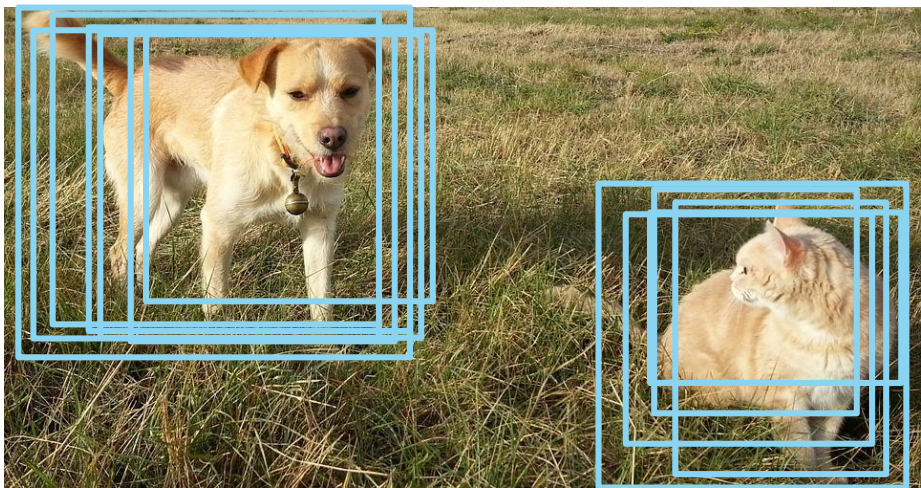
Gidaris, Spyros, and Nikos Komodakis. "Locnet: Improving localization accuracy for object detection."

“If we pick better priors for the network to start with we can make it easier”

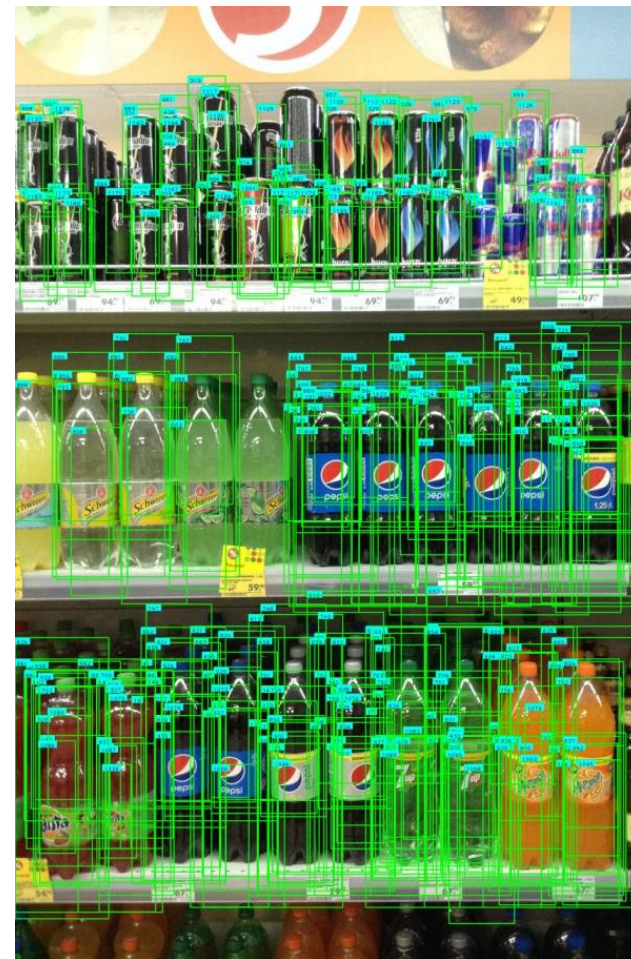
Redmon, Joseph, and Ali Farhadi. "YOLO9000: Better, Faster, Stronger."

Duplicate Merger

The “Standard” Case



Our Case



Are these products cans?

No!

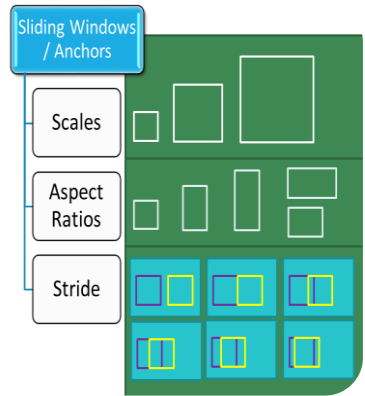
Really
Not

Yes!

Not
Really



Detector Innovations - Poster



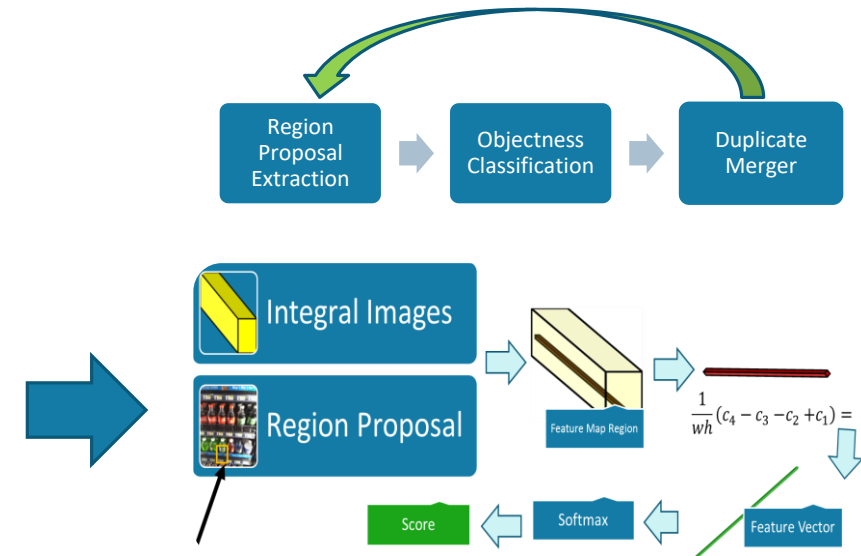
Region Proposal Network



Objectness Soft Labels



Robust Duplicate Merger



O(1) Region Classification

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Take Home Message

- **Fine-grained Classification is Challenging**
- **New Context Embedding CNN Architecture**
- **NLP Inspired**
- **Detection challenge**

Trax

image recognition

Thank You

