

The logo for the 2021 Embedded Vision Summit Virtual. It features the year '2021' in a light blue font at the top. Below it, the word 'embedded' is in a smaller, dark blue font. The word 'VISION' is in a large, bold, dark blue font, with the letter 'O' replaced by a colorful circular graphic composed of many small dots. Below 'VISION' is the word 'summit' in a dark blue font. At the bottom, the word 'VIRTUAL' is in a green font, followed by a vertical bar and the dates 'MAY 25-27' in a light blue font. The entire logo is set against a white background with a faint grid pattern, which is itself centered on a larger graphic of overlapping green and yellow triangles.

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Automated Neural Network Model Training: The Impact on Deploying and Scaling ML at the Edge

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SeeWare Platform



Smart Streets



Retail



Smart Buildings



Healthcare



Traffic Management

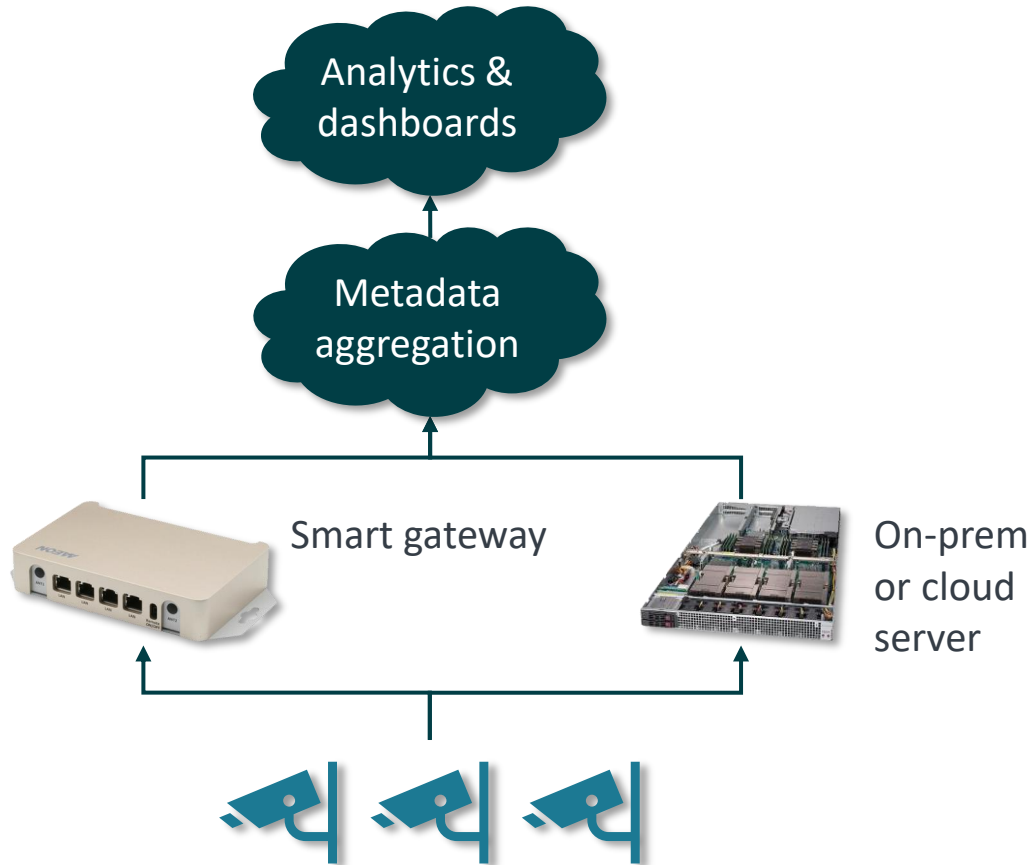
Edge-to-cloud model for CV applications

- Multiple sensors: typically cameras
- Local smart gateways / on-prem servers
- Running detection models & streaming insight metadata into the cloud
- Cloud aggregation with analytics & dashboards

The challenge now is how you scale

- Many real-world use cases need models to be built or tuned in real time

We're going to look at a two examples of how we can start to **automate** model creation & tuning



The typical understanding of federated learning:

- Spreading a model training pipeline across multiple edge devices

This talk is more accurately looking at learning from federated training data

- Cloud aggregating training data gathered from multiple edge devices to train / tune models that can be redeployed back to the edge via over-the-air updates

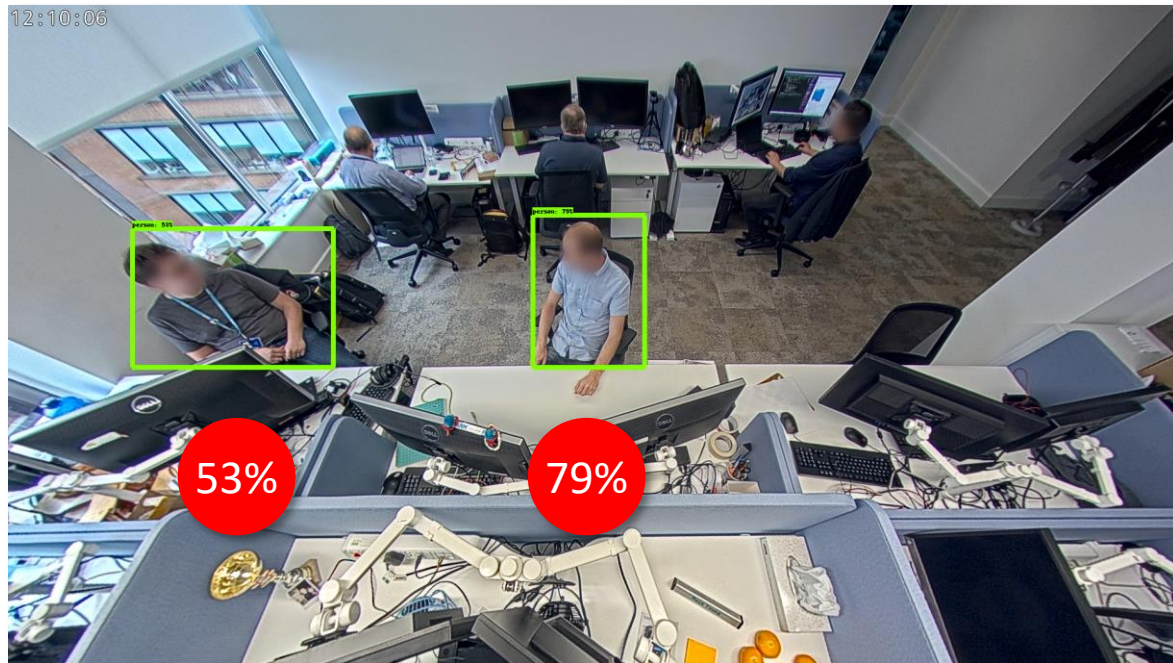


Example 1: Auto Model Tuning

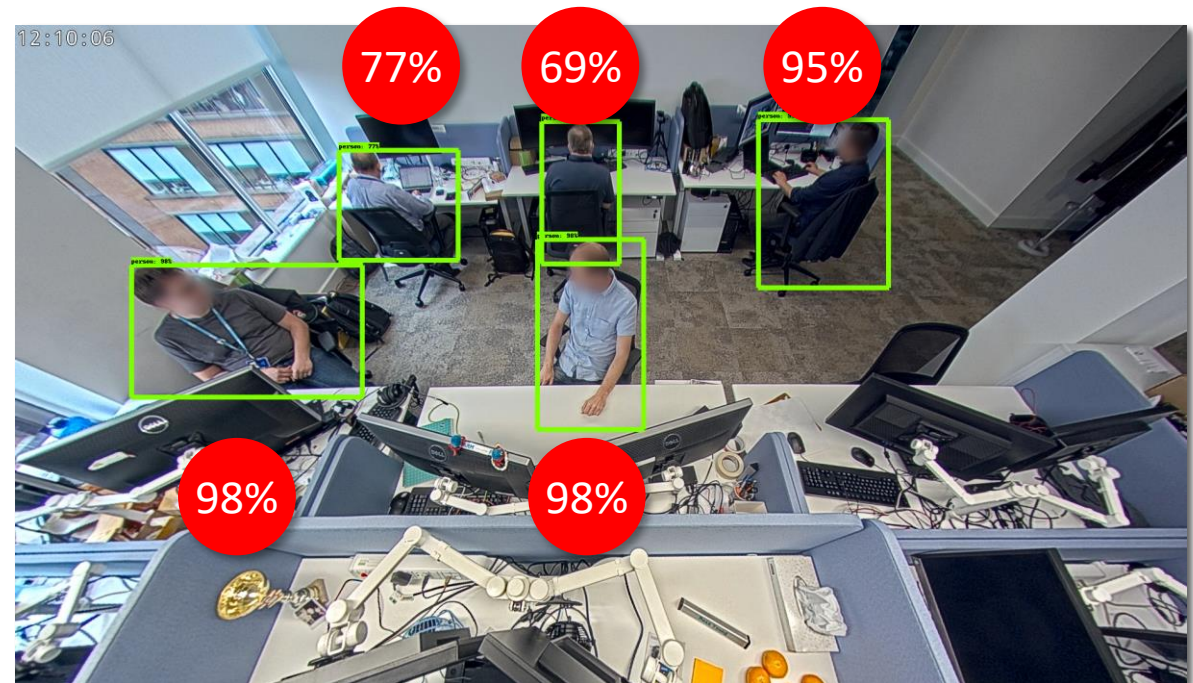


Comparison of Detection Performance

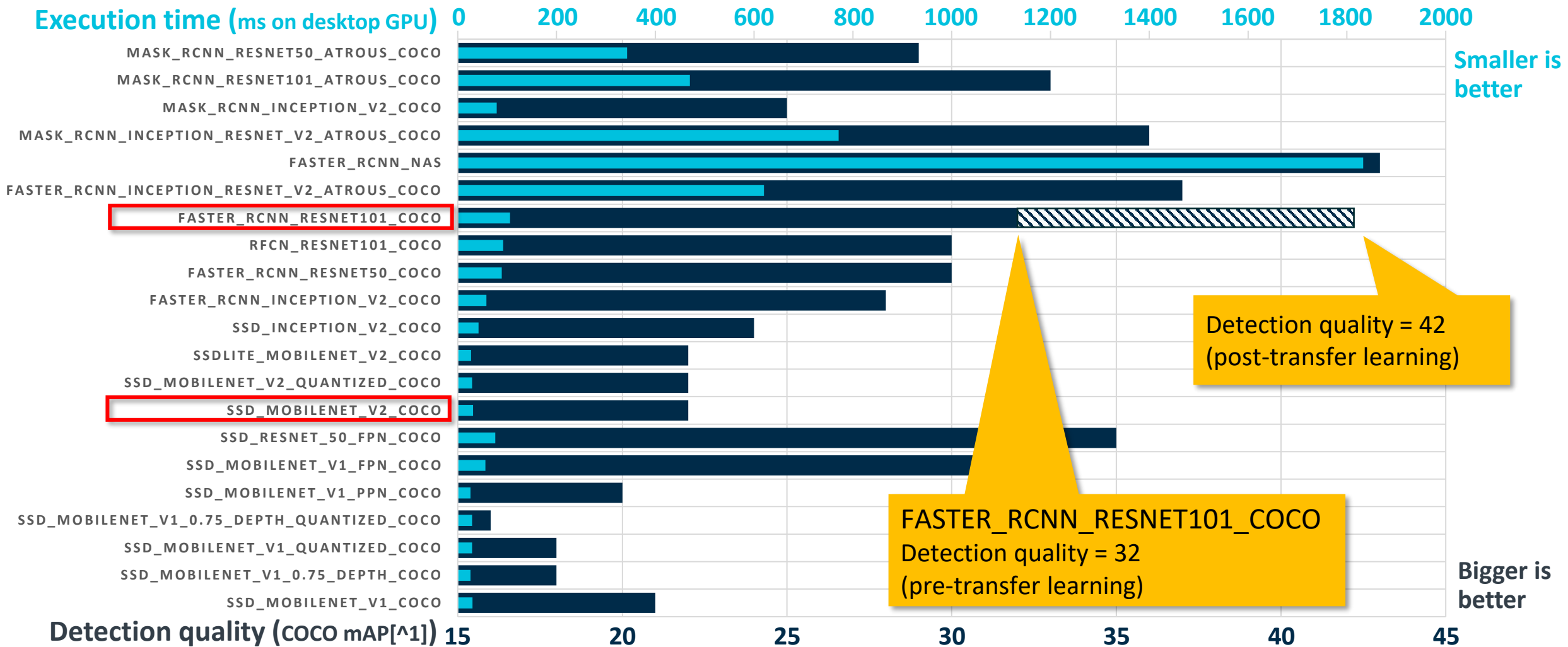
SSD_MOBILENET_V2_COCO



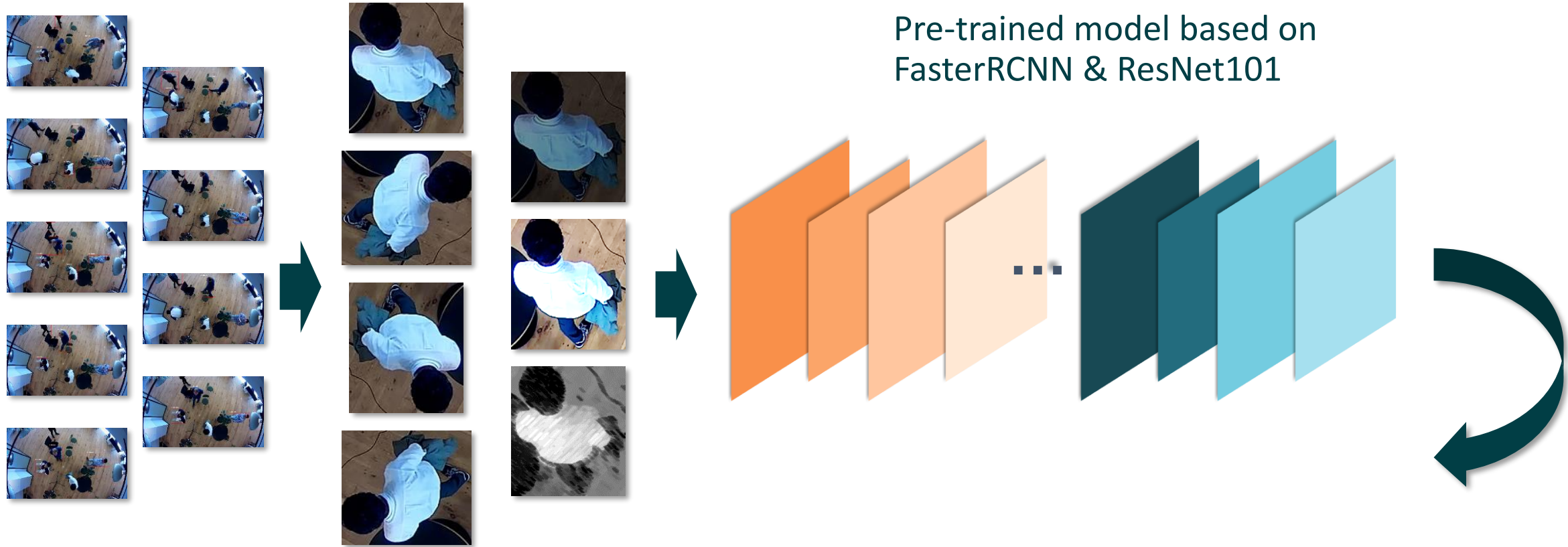
FASTER_RCNN_RESNET101_COCO



Impact of Transfer Learning



Tuning the Model Using Transfer Learning



Gather and label new set of sample images (~250)

Crop & create rotated, brightness, quality variations

Pre-trained model based on FasterRCNN & ResNet101

Feed through training pipeline using existing network

Repeat for each image

Transfer Learning for Model Tuning. Does it Scale?

In practice, what does model tuning involve?

- Gathering training data (100s to many 1000s of images)
- Image labelling
- Running the training process

Bottom line: model training is a time-consuming, laborious process

- Difficult to scale to multiple locations
- Particularly if the tuning is a requirement to take in conditions specific to each location

For many use cases this just won't be viable

- Unless you can automate the process, ROI is going to be hard



Multiple Thresholds

Set detection threshold T1

For detections $\geq T1$, assume **true positive**
For detections $< T1$, assume **true negative**

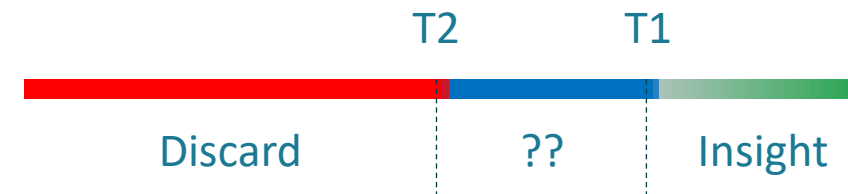
e.g. $T1 = 75\%$...



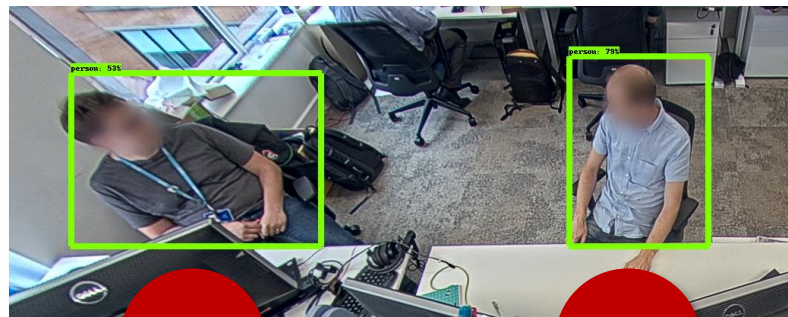
Set additional threshold T2, where $T2 < T1$

For detections $< T2$, assume **true negative**
For detections between T1 & T2, assume **item of interest**

e.g. $T1 = 75\%$, $T2 = 50\%$...

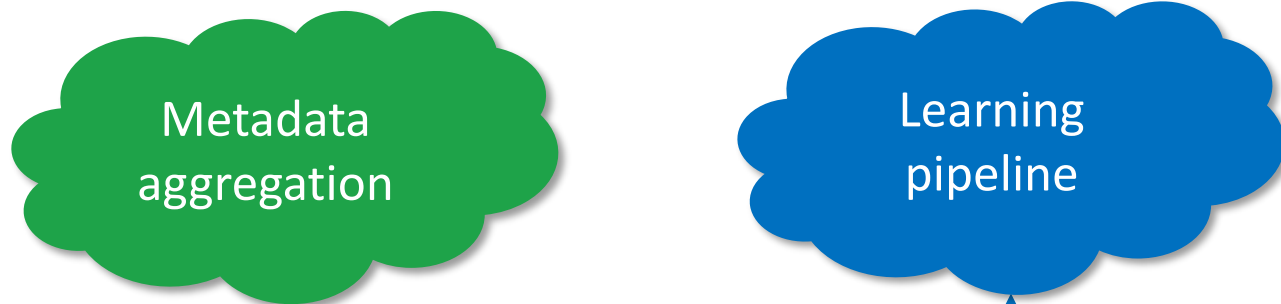


SSD_MOBILENET_V2



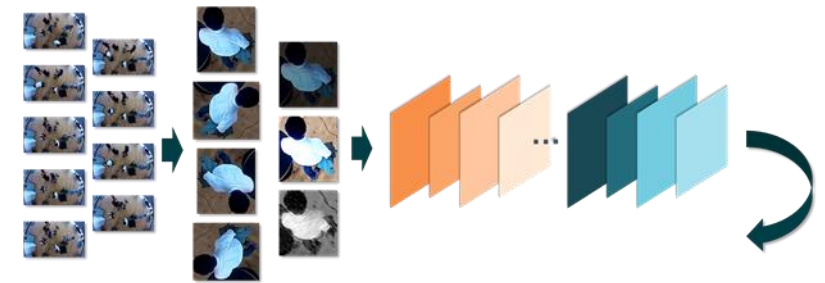
53%

79%



Learning Pipeline

1. Put images received through cloud model (e.g. **FASTER_RCNN_NAS**)
2. If detections above set threshold $T3$, then add image to true +ve list
3. Periodically, use transfer learning pipeline to tune the edge model with the collected true +ve images

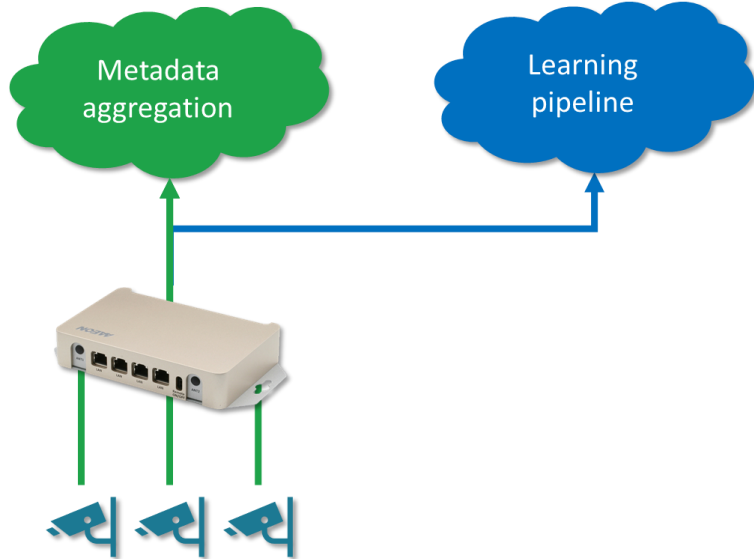


4. OTA update model back to edge gateways

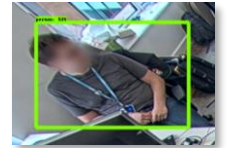
Could We Go One Step Further?

What if the cloud model also had two thresholds (T3 & T4)?

Human aggregation when there is still uncertainty to improve the cloud model



$T4 \leq \text{confidence} < T3$
+ frame grab and
detection bounding boxes



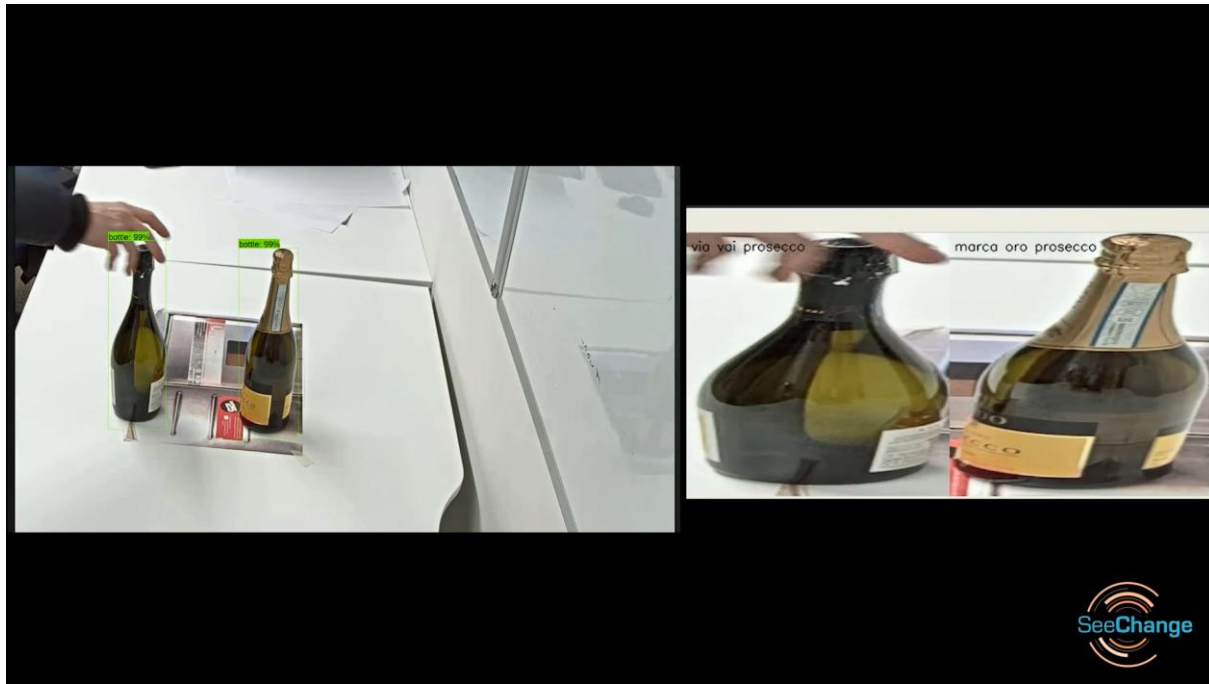
A cascade of re-training

1. Human aggregation on a relatively small number of images helps to tune the cloud model
2. The cloud model helps to tune the edge model



Example 2: Zero Touch Model Learning & Tuning





<https://youtu.be/S6tAprp-bUU>

Helping reduce retail product shrink

Reconcile two lists

- What is seen vs what is scanned
- And alert if there is a discrepancy

Uses a standard object recognition model

- Product recognition works well

But how does this scale?

- Who trains the model?
- What happens when product packaging changes?
- Serious risk in reduced ROI if this process cannot be automated

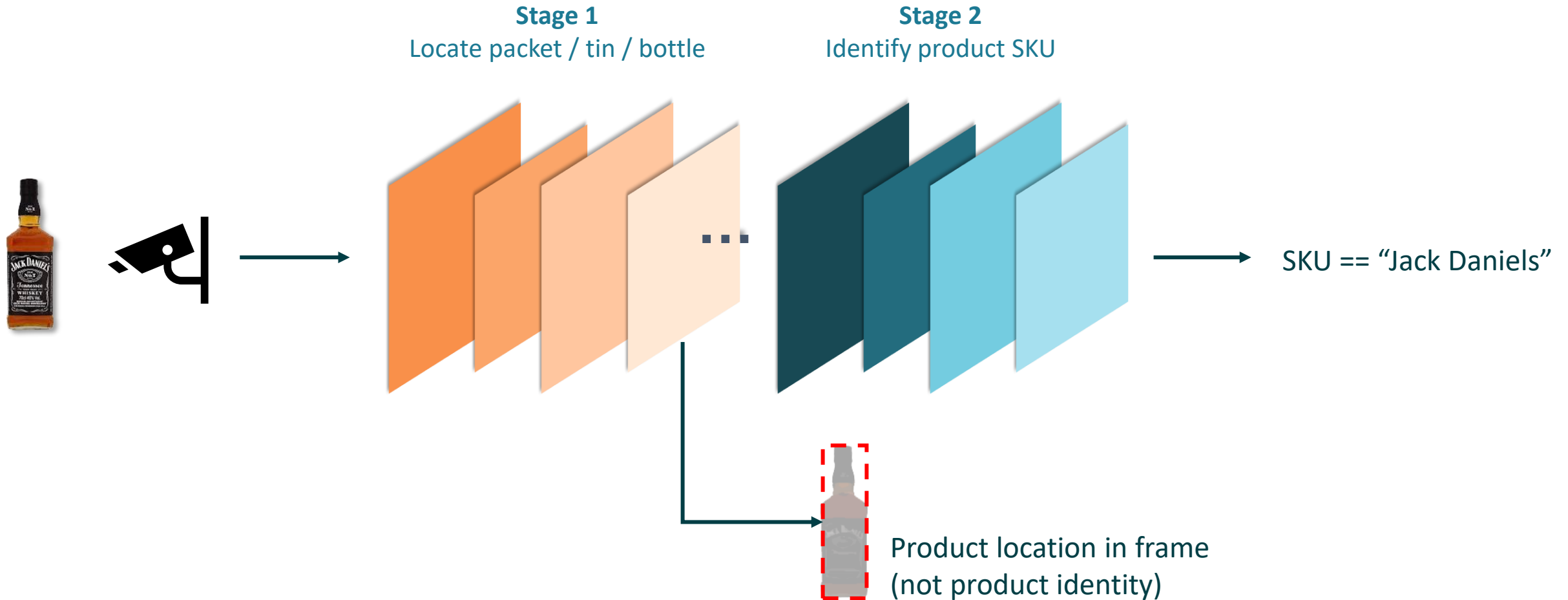
Training for New Products: The Manual Approach



Image capture pipeline:

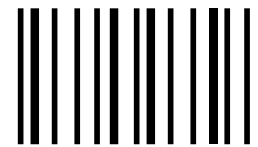
- Scan the product's barcode to register it with the existing stock database
- Put product into capture area
- Rotate the product whilst taking pictures
- Using transfer learning, the images retrain the machine learning model so the new product can be recognised

Automation: Getting More from your Model Pipeline



Using Honest Transactions to Train our Model

Honest transactions create ground truth we can use for product training



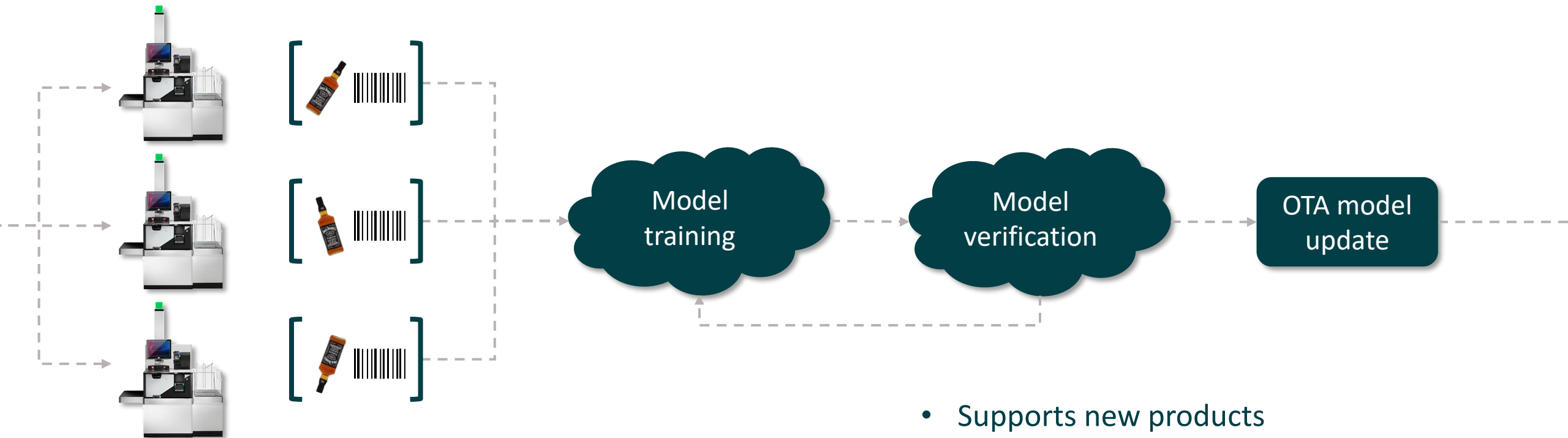
+ timestamp



With the timestamp from when something we didn't recognise was scanned we can find the associated product bounding box

Training data

Bringing Everything Together in the Cloud

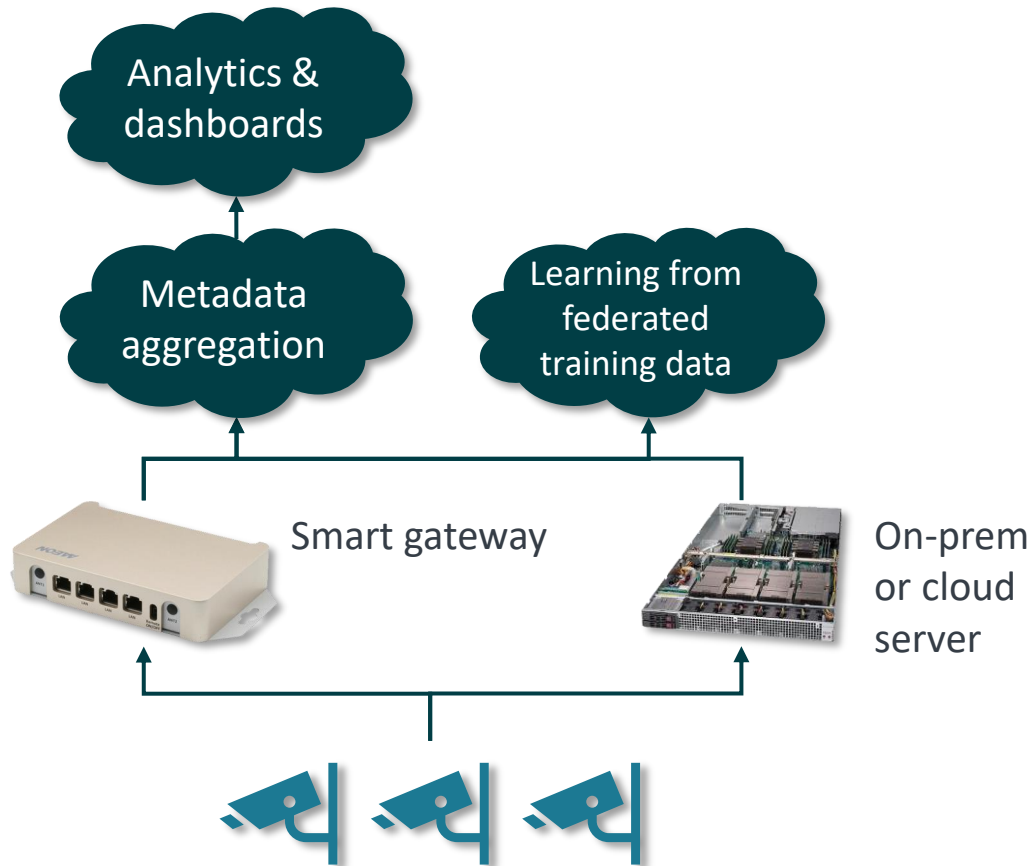


- Supports new products
- And products with updated packaging
- **Zero** touch for the supermarket



Enabling Auto Learning: Making it Easy





The edge-to-cloud architecture to support auto learning can be complex

- Potential additional complexity at the edge
- Cloud infrastructure to handle incoming training data
- In-cloud retrain & testing pipeline
- OTA deployment back to edge devices

Commoditizing these abilities is essential

- Reducing the friction for their use
- Allowing applications to leverage the significant benefits of auto-learning

Summary: Look for More at the Edge

Scaling & deployability are the new challenges

- ML and CV are becoming commoditized
- Now we need to do the same for auto-learning

Get more value from your edge cameras

- The more ground truth you can gather, the more your applications can self-learn
- This potentially challenges the design of the models we run at the edge: but the ROI payback is significant

Keep an eye on privacy

- Sending imagery into the cloud for training may effect your Data Privacy Impact Assessment (DPIA)



Resources

Tackling Product Recognition at Checkouts Using Neural Networks

Fanioudakis, Patel

<https://seechange.ai/product-recognition-part1/>

How AI Can Take The Drudgery Out Of Tuning Machine-Learning Models

(Forbes) Zeichick

<https://bit.ly/2Q5Uksw>

7 Jobs Humans Can Do Better Than Robots And AI

(AI won't replace soft skill jobs... do you agree?)

(SmartDataCollective) Mallon

<https://bit.ly/2REWbF6>

2021 Embedded Vision Summit

“IoT and Vision: Why It’s a Security Minefield and How to Navigate It”

Lyndon Fawcett

SeeChange Security Architect
Wednesday 26 May, 10:30am

