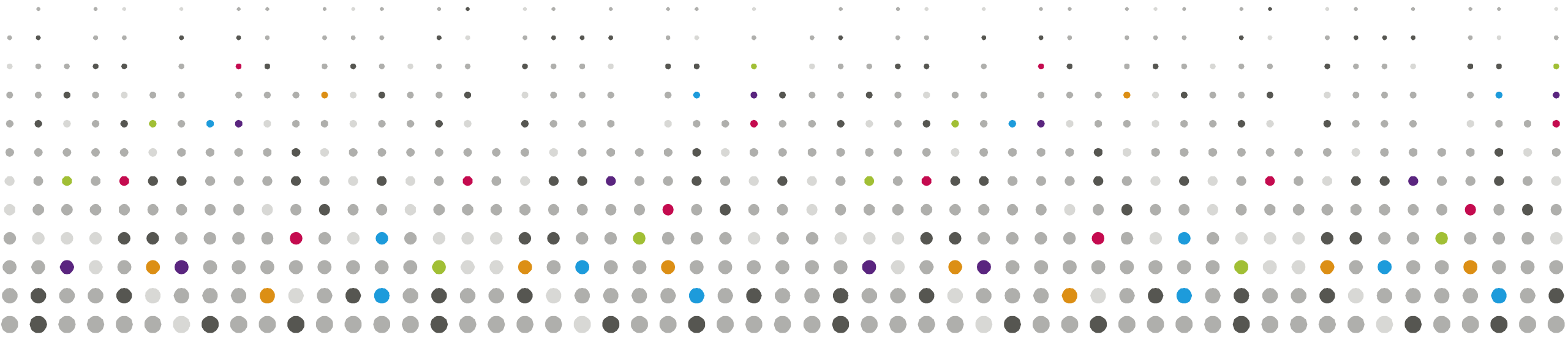


Bridging the gaps: Deep learning to the manufacturing electronics factory line

Speaker: Javier Cabello



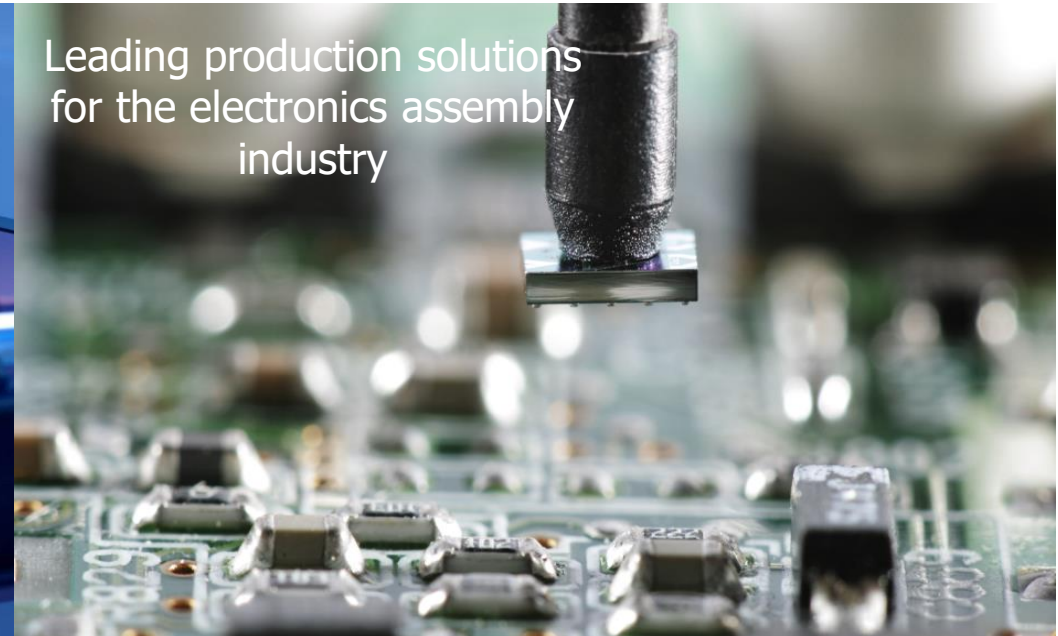
Mycronic

Two business areas serving the electronics industry

Pattern Generators



Assembly Solutions



CENTER FOR DEEP LEARNING IN ELECTRONICS MANUFACTURING

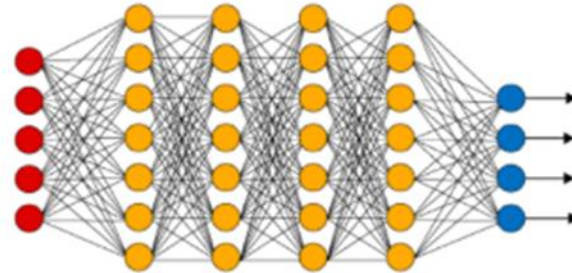
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Industrial leaders with
shared domain
knowledge

Technical expertise
within deep learning

Faster addition of business
value:

Knowledge + increased
performance

Machine learning paradigm

“Data is the new code”

Traditional programming

- A relatively easy set of rules works for say 99% of the cases.
- Solving the rest 1% can take 90% of the programming effort.



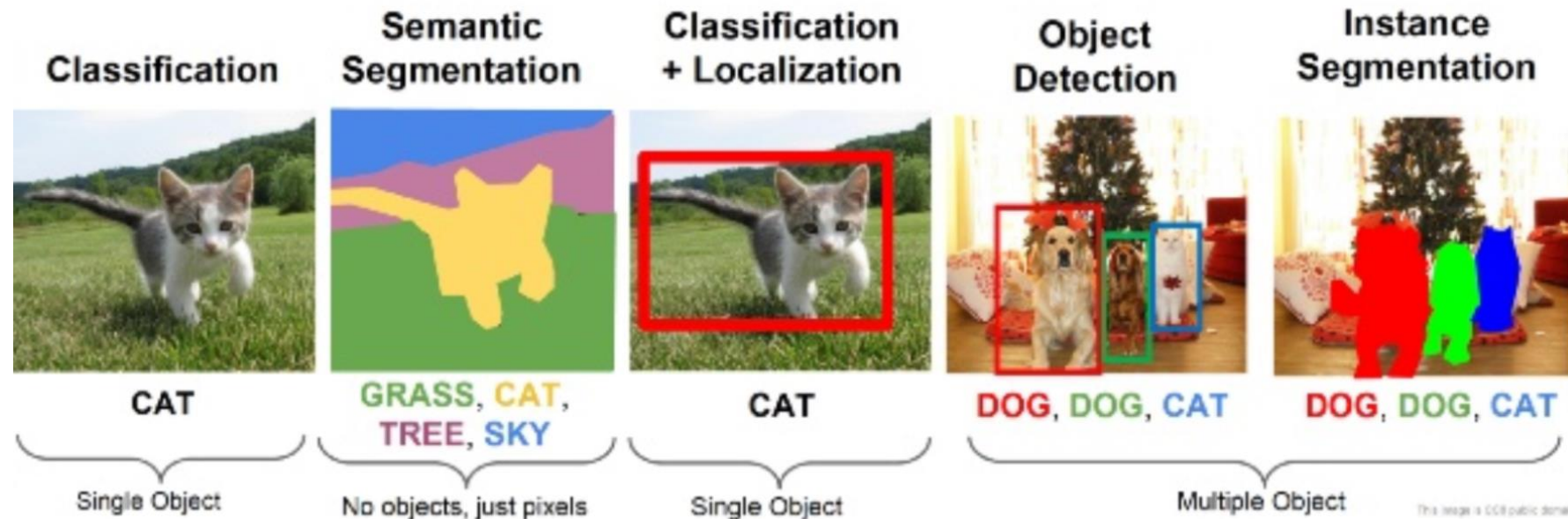
Machine learning

- These 1% of odd cases can often be easy to collect
- Just feed the new data to the training of deep learning algorithms which will generate a new set of rules



Supervised machine learning

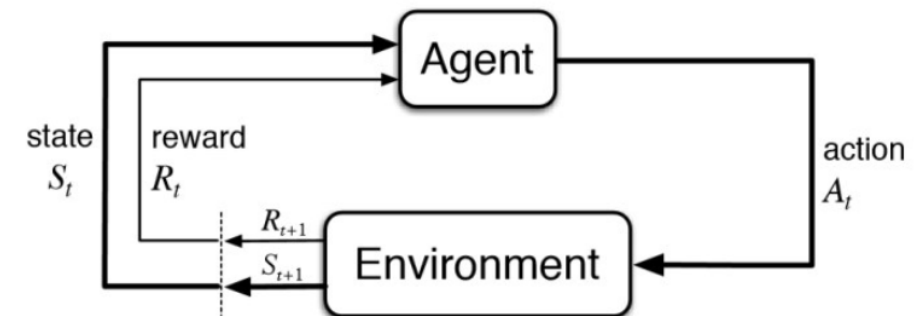
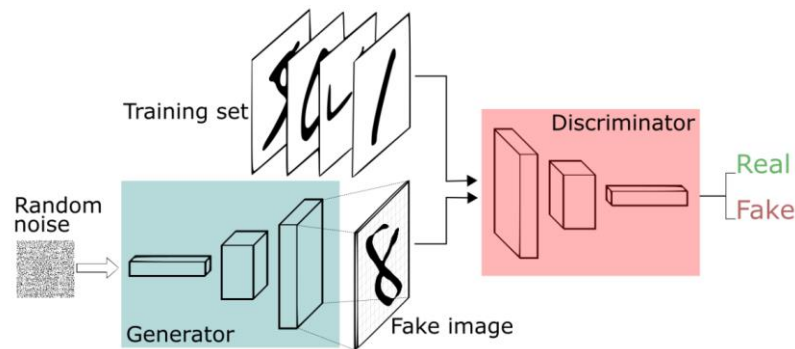
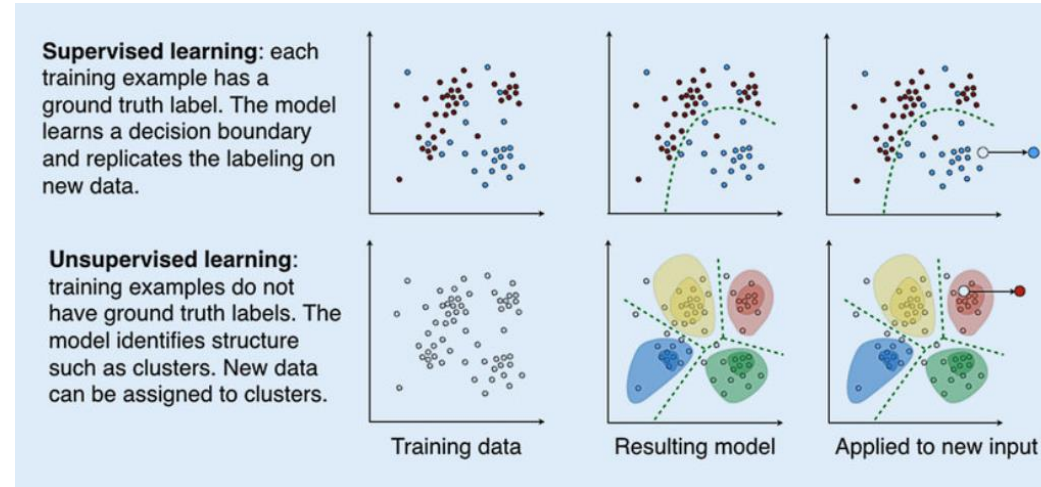
Annotation (even assigning labels) usually is expensive and error prone or ambiguous



from: Stanford University 2016 winter lectures CS231n Fei-Fei Li & Andrej Karpathy & Justin Johnson

Non supervised machine learning

Unsupervised, generative deep learning and reinforcement learning



Which problems can be targeted better with deep learning?

List of projects/ideas

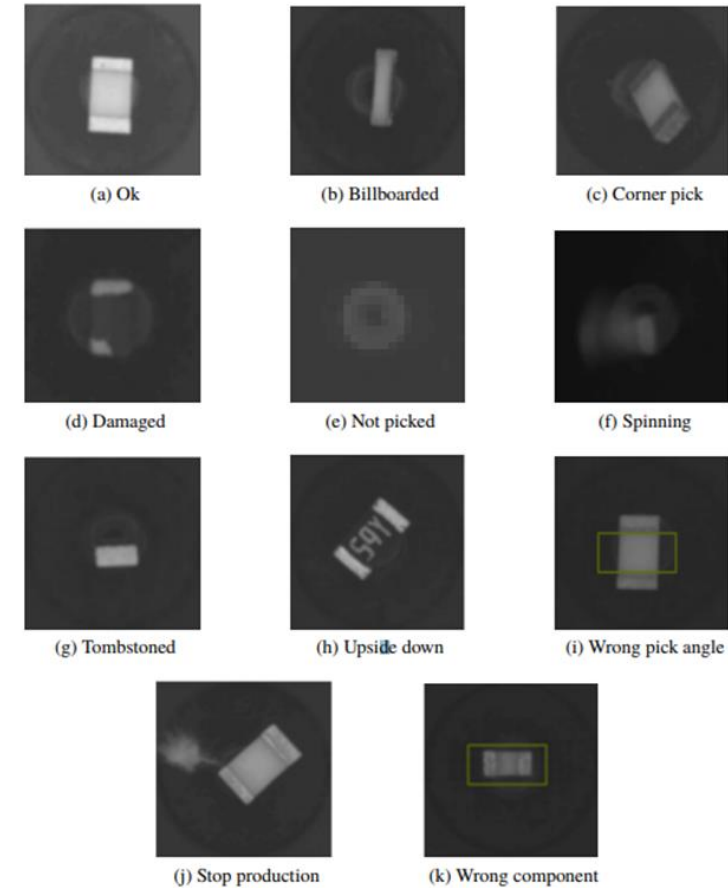
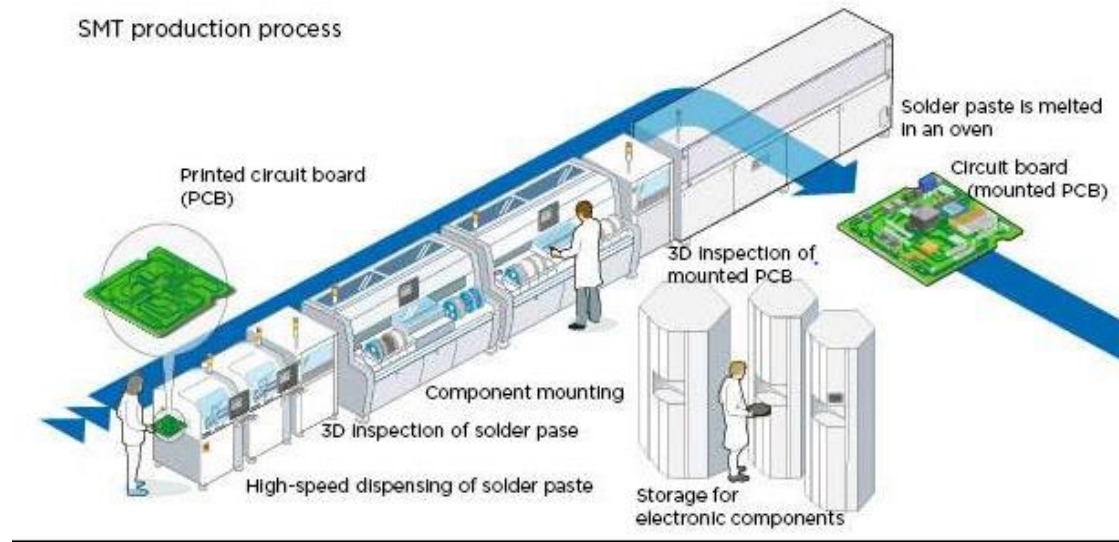


Bridging the gaps

1. Missing data
 - Store the data when available, not when needed
2. Good annotation is expensive
 - Use simulations and other generative methods when possible
 - Invest in good annotation tools
3. Computing and storage resources
 - For training (infrastructure)
 - For inference at the edge
4. Know-how
 - Expertise and transfer learning

Bridging the gaps: Collecting data

Change mindset: Collect the data before you think you need it

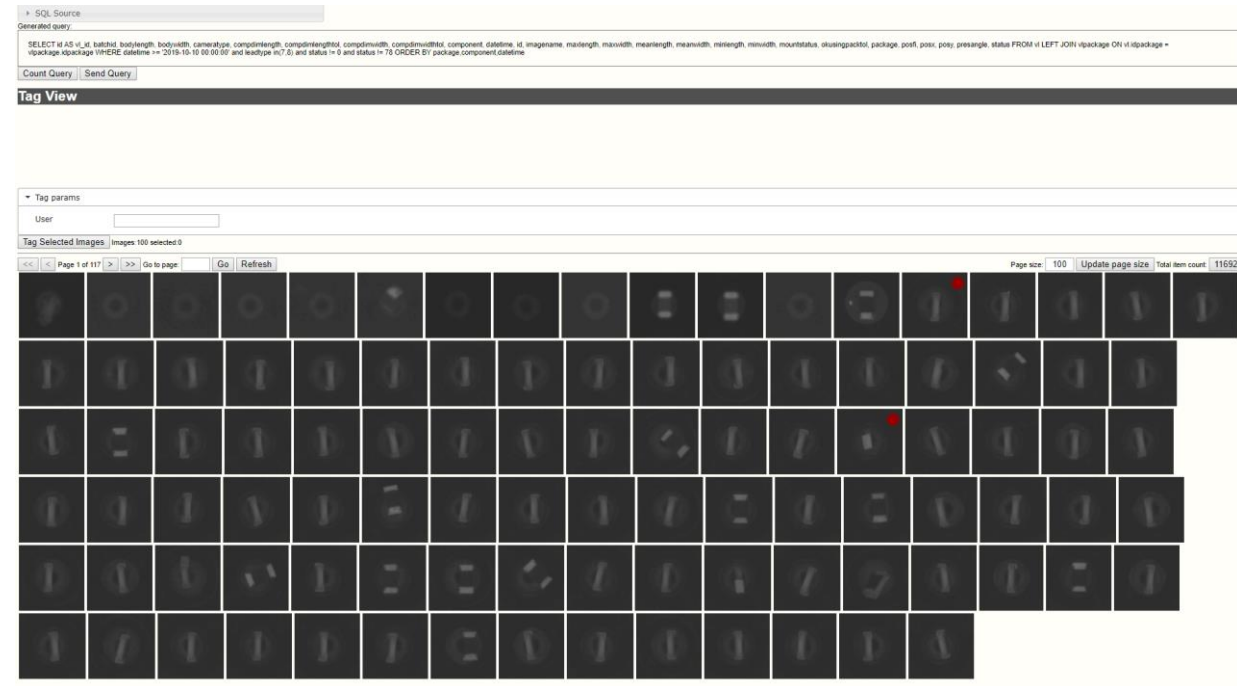


Bridging the gaps: Annotating the data

Invest in tools that help to structure, annotate and select the data for training

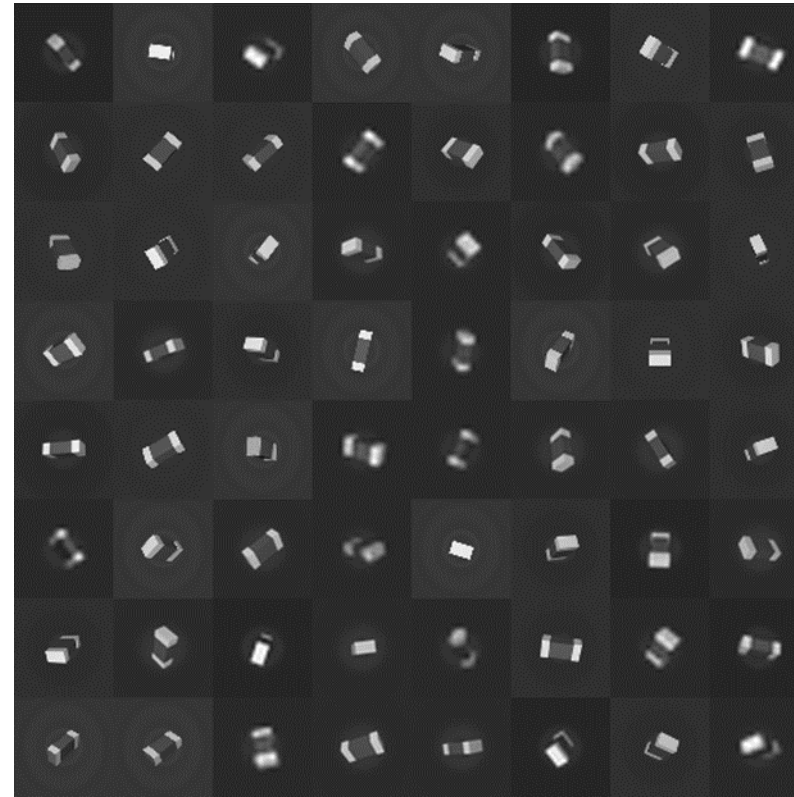
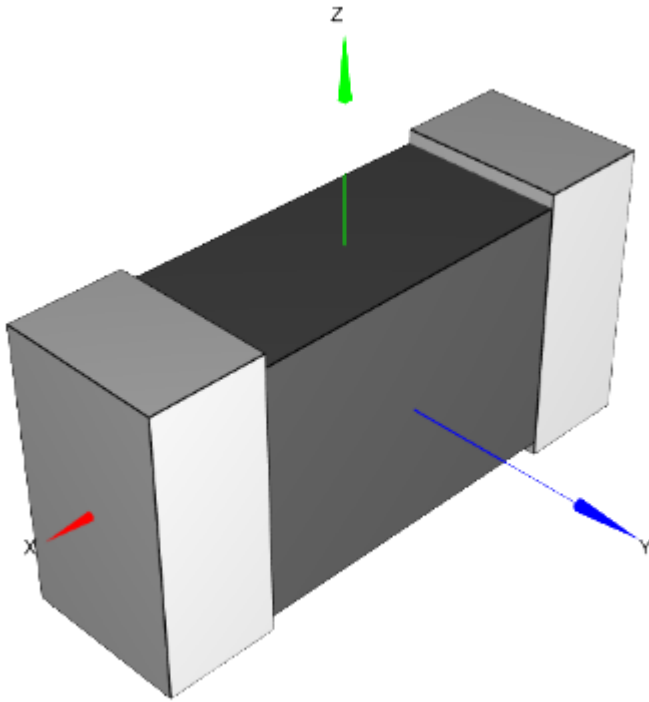
“More data beats better algorithms”:

- Odd cases might be difficult to either collect or simulate but are a success factor
- Annotation is expensive and human error prone but...
- Deep learning is robust to non-systematic annotation errors



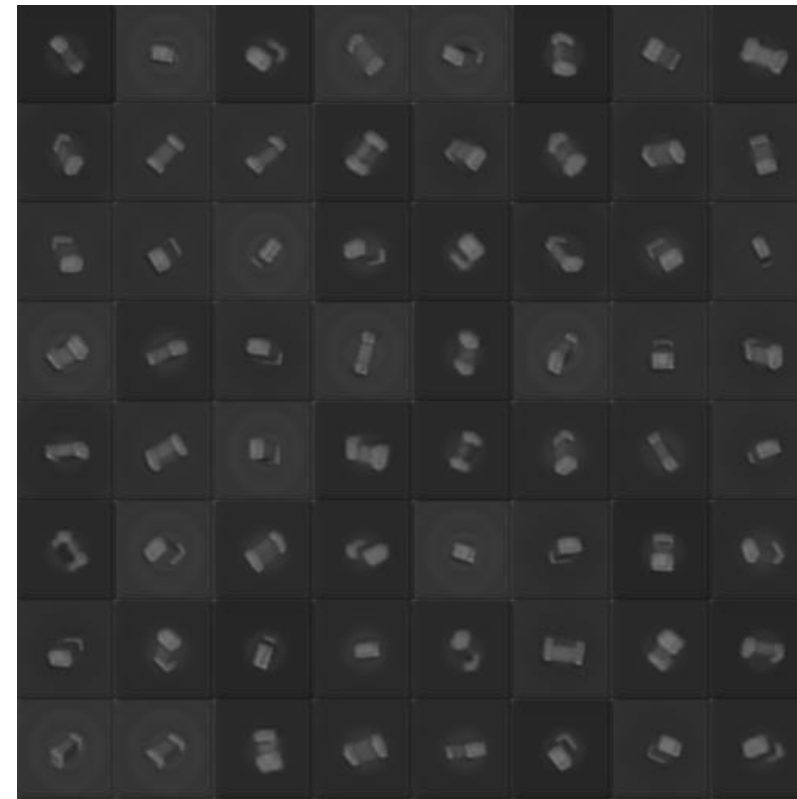
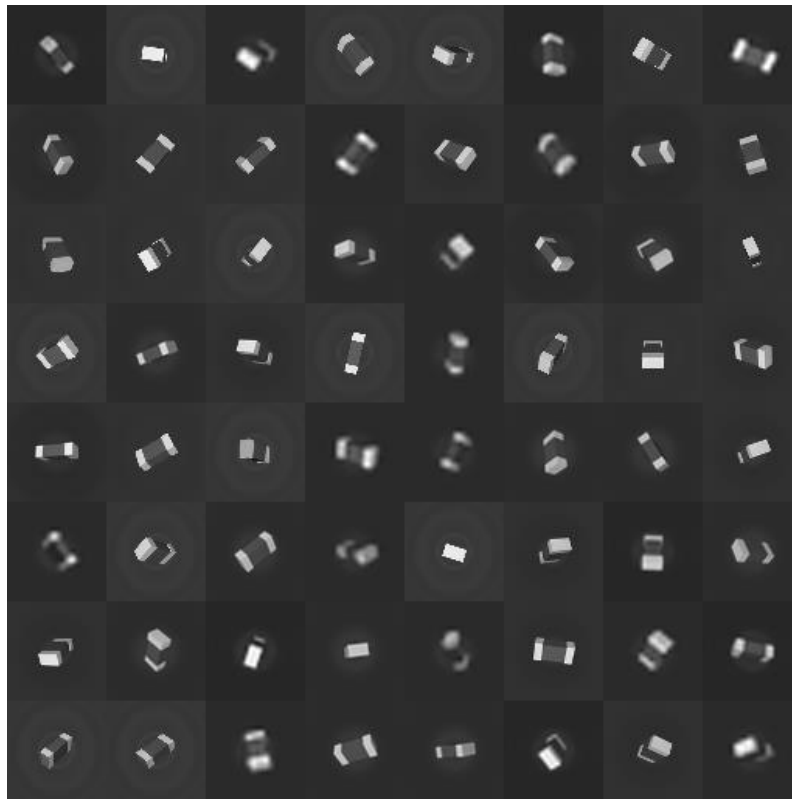
Bridging the gaps: Augmenting the data

Creating simulations for rare cases (that you can figure out 😊)



Bridging the gaps: Augmenting the training data

From simulations + generative models: you get the annotations for free



Bridging the gaps:

Collaboration and share of computing and know-how resources in Silicon Valley



CDP38:
4000 TFLOPS of computing
performance

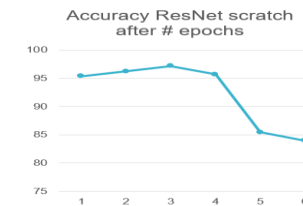
Associative Domain Adaptation and ResNet-50 without TL

Resnet-50 trained from scratch gives lower accuracy (best 97,16 % after 3 epochs) and hints also overfitting

Reproduced results from Associative Domain Adaptation

- ADA with subset of small chips (original assignment): 99,64 %
- ADA with same test set as in @CDLE: 99,49%

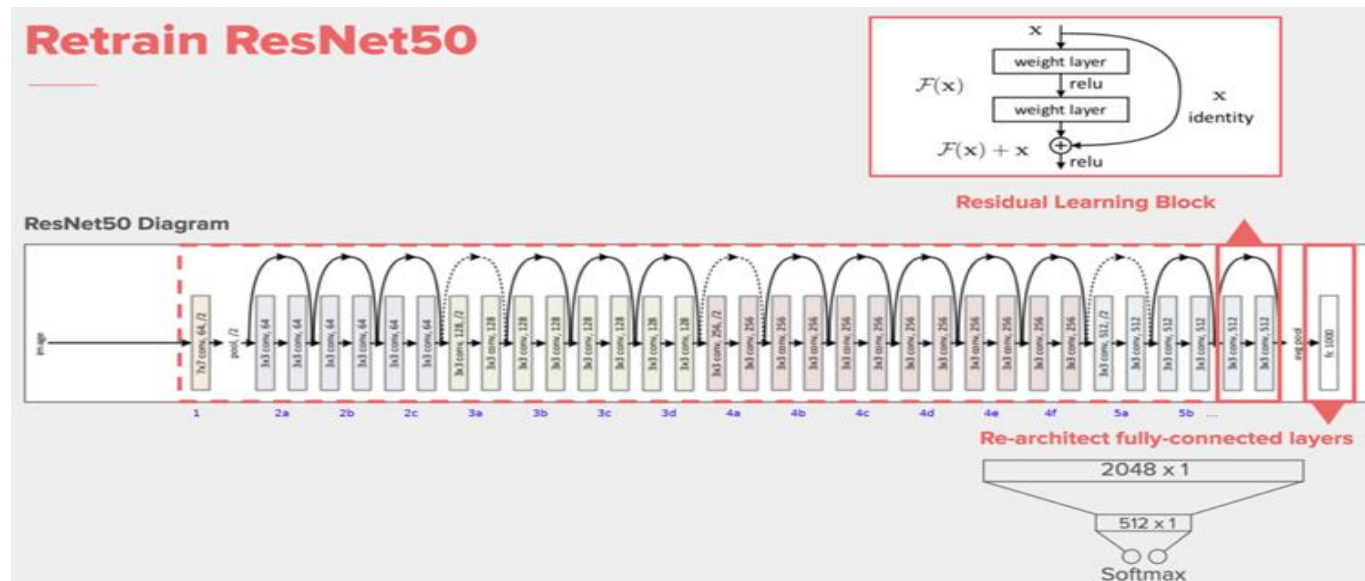
Best ADA network is recorded at epoch 2 (of 8)



Bridging the gap: Know how

Transfer Learning

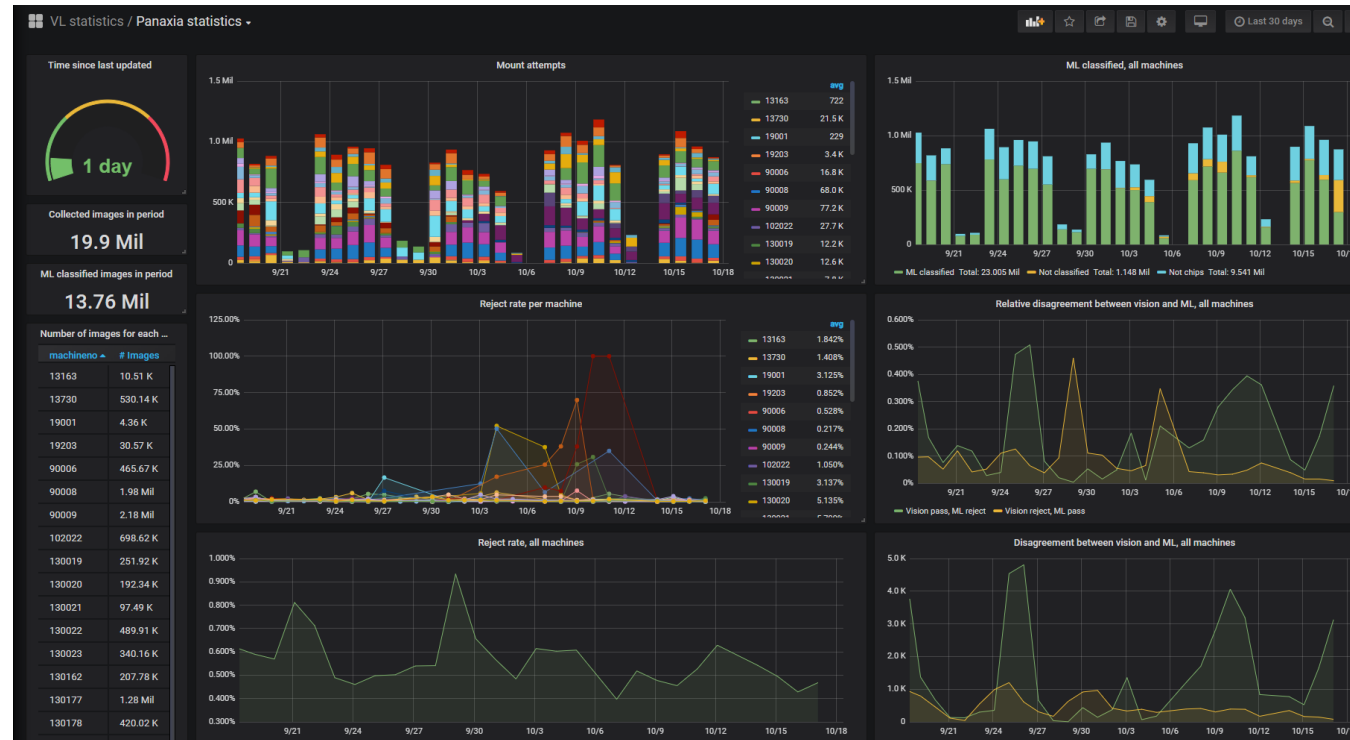
- For many tasks the rules generated for solving a task generalize well to other tasks by just retraining the neural network with fewer data samples from the new task.
- Only some layers of the network are retrained ("finetuned") depending on how much the data sets differ
- Specific requirements on the industry:
 - Very high accuracy: At least close to on par with current performance
 - Gathered data sets are very skewed: Many samples of OK cases compared with NOK



Creating business value

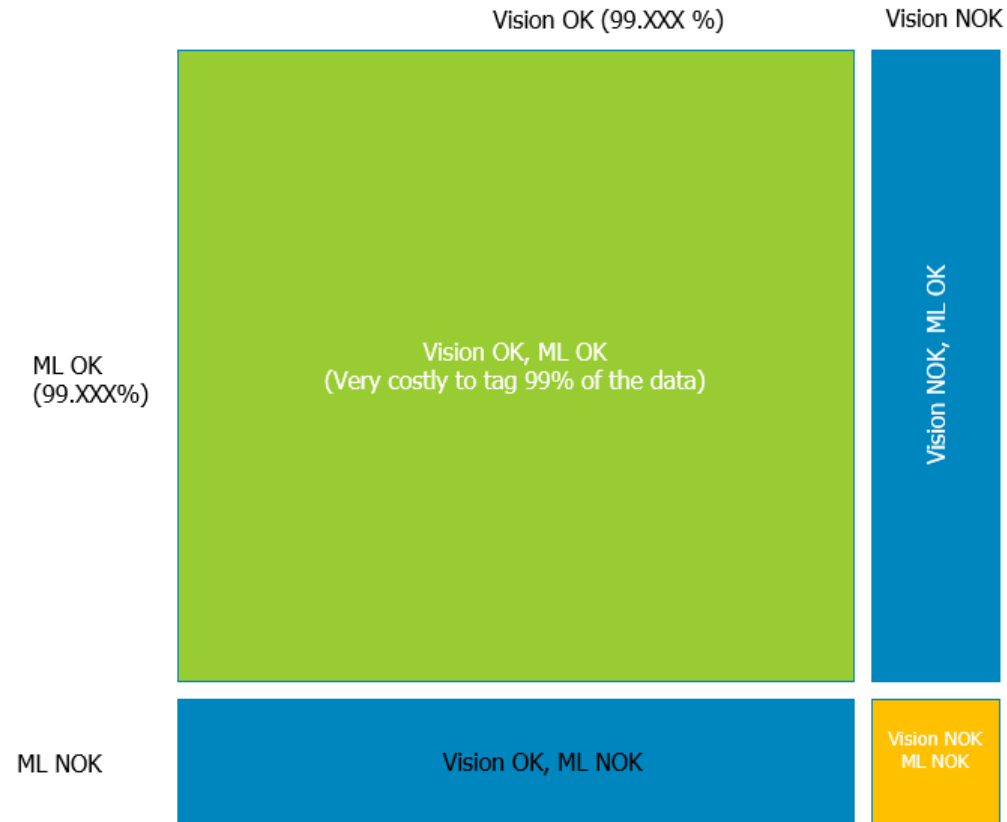
Measuring current system performance without relying on other machines

- We can roughly compute errors made by the Pick & Place machines by annotating much fewer images (1/1000 of the total)



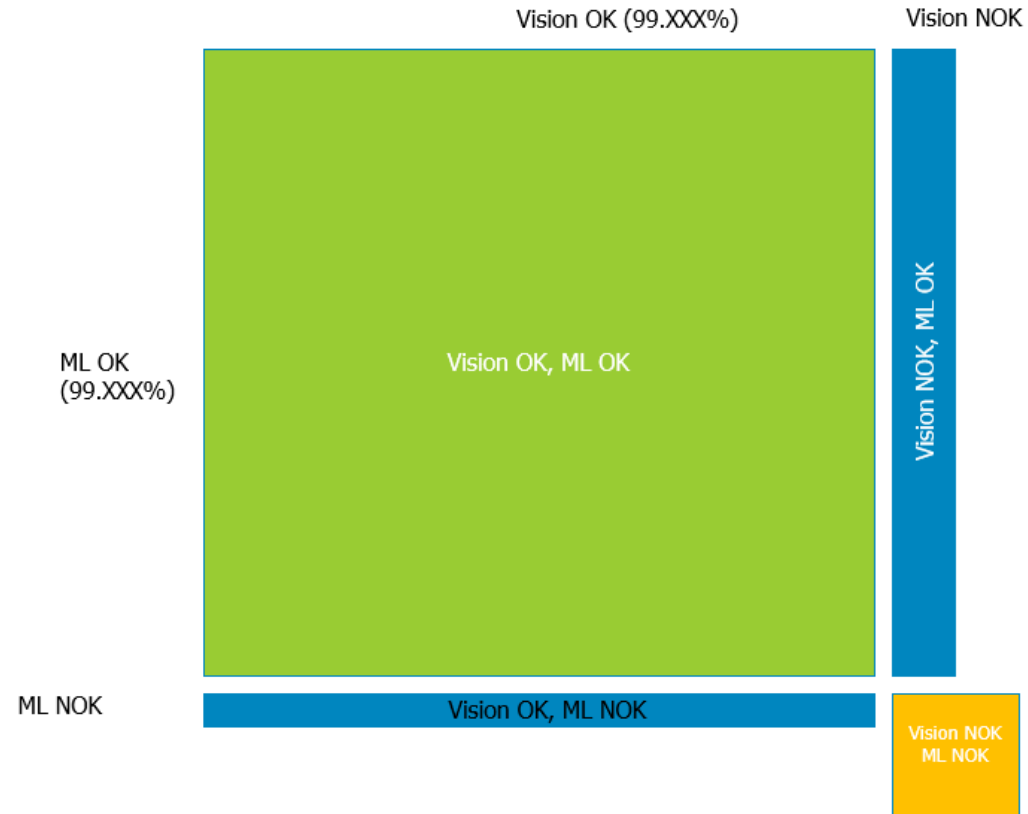
Creating business value: Enhancing performance

- Accuracy requirements are very high but we can take advantage of already very accurate processes



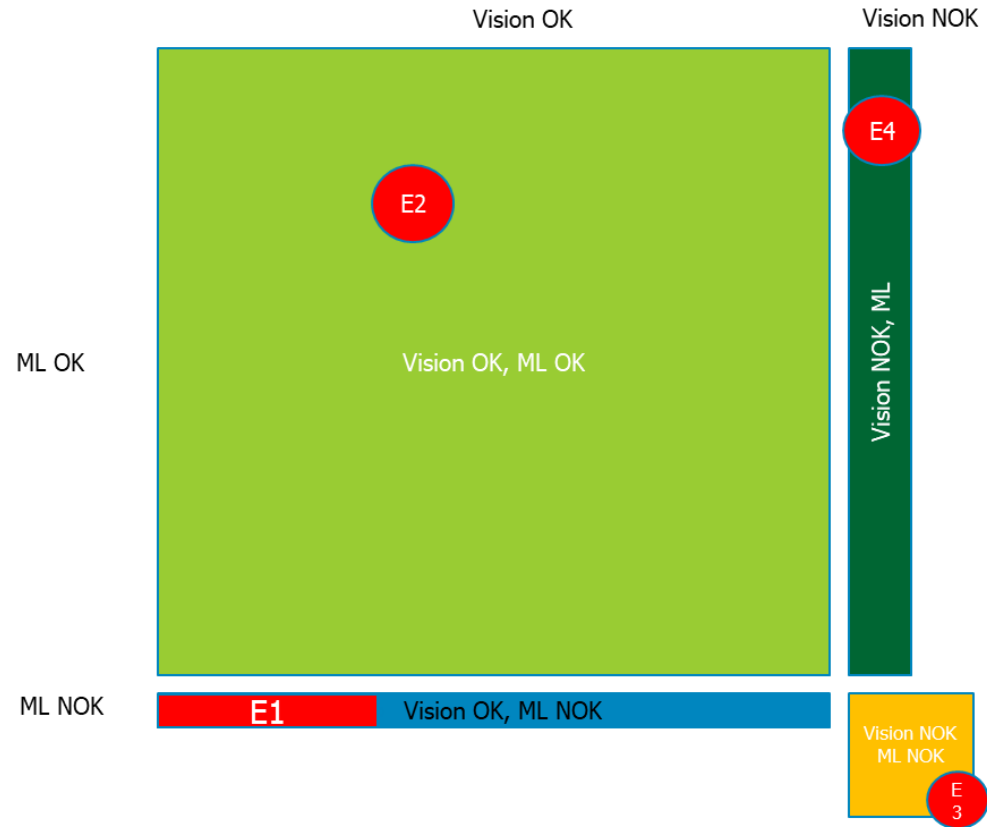
Enhancing performance

- Deep learning models have to match to a very high extent current image analysis processes as we know they already very accurate.
- This allows us to disregard DL some algorithms without needing to tag huge amount of data



Creating business value: Enhancing performance trade-offs

- Detect as many possible False Positives at the cost of as low as possible False Negatives
- First results show FP reduced by $> 50\%$ (expensive errors) at the cost of FR increased by $< 20\%$ (cheaper errors)

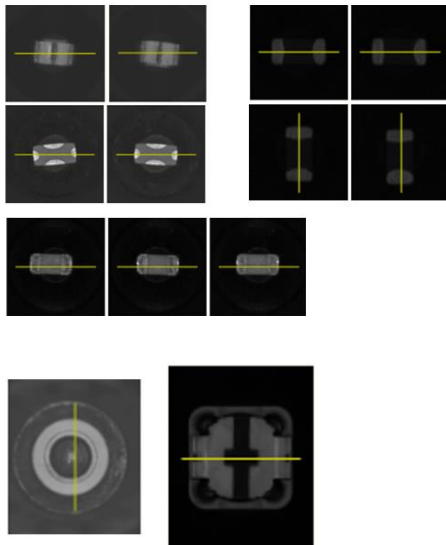


Deployment issues

Reliability and performance

When to let DL be part in the decision making

- Never seen data in the training process is likely to be classified incorrectly.
- But if performance of current process and DL is close or better than already very accurate systems you can start trusting DL for specific tasks



Performance without losing accuracy:

- Model compression techniques
- Plug-in HW accelerators



Deep learning is here to help us to take the next leap in electronics manufacturing process reliability



Thank you for listening!