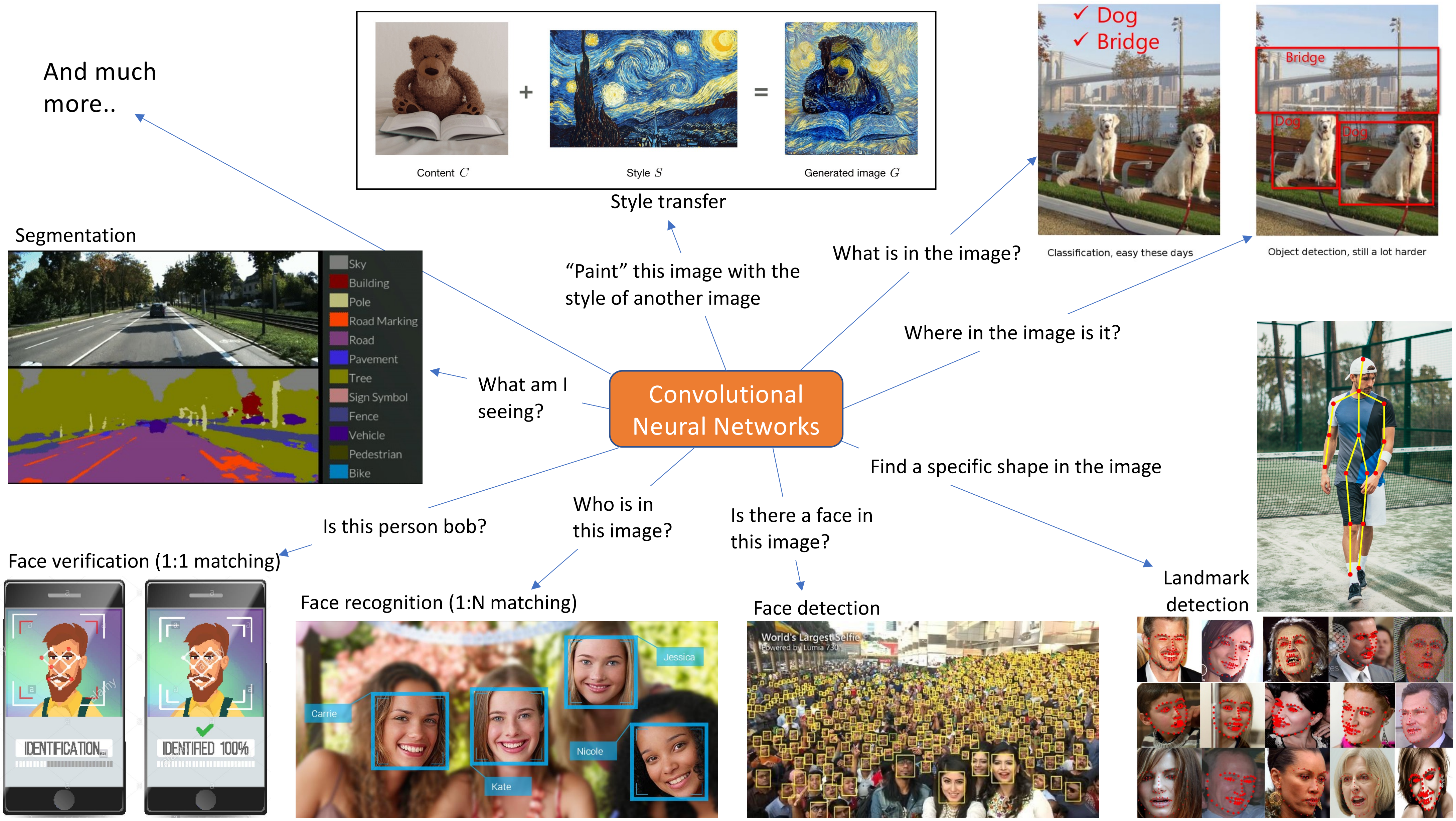
Kjersti Engan, professor, leder of BMDLab , Dept. of electrical engineering and computer science

Supervised, unsupervised, semi-supervised and transfer learning

ELE 680 Deep learning

University of Stavanger

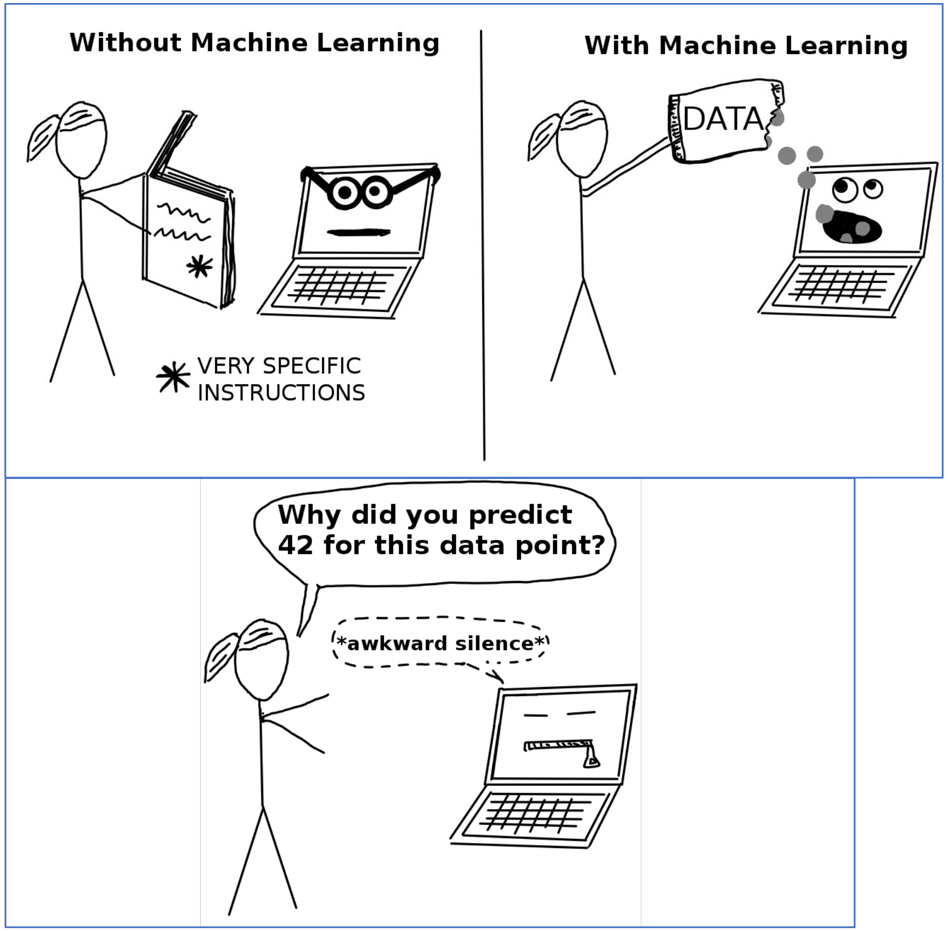
08/07/21



Convolutional Neural Networks
Content C
Style S
Generated image G
Style transfer
"Paint" this image with the style of another image
✓ Dog
✓ Bridge
Classification, easy these days
Bridge
Dog
Dog
Object detection, still a lot harder
What is in the image?
Where in the image is it?
And much more..
Segmentation
Sky
Building
Pole
Road Marking
Road
Pavement
Tree
Sign Symbol
Fence
Vehicle
Pedestrian
Bike
What am I seeing?
Find a specific shape in the image
Landmark detection
Is this person bob?
Face verification (1:1 matching)
IDENTIFICATION...
IDENTIFIED 100%
Who is in this image?
Face recognition (1:N matching)
Carrie
Kate
Jessica
Nicole
Is there a face in this image?
Face detection
World's Largest Selfie
Powered by Lumia 730

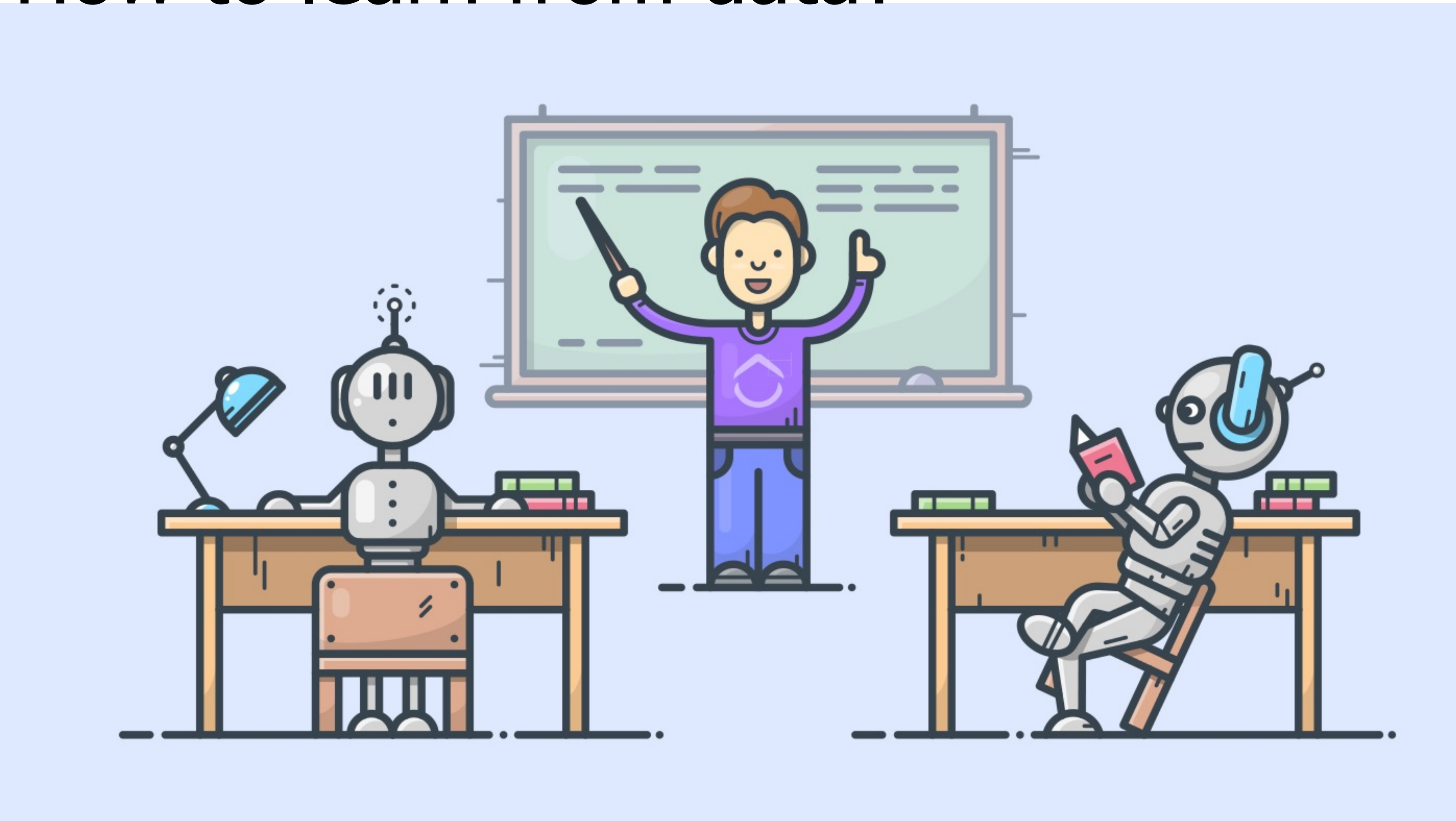
What did we do before Machine Learning?

- We had to have/develop good models and theories on what we wanted to do with our input.
- We made algorithms for the computer to go through
- With Machine learning we let the computer learn many of the connections itself.
- Disadvantage: It is harder to interpret the results.



https://christophm.github.io/interpretable-ml-book/terminology.html

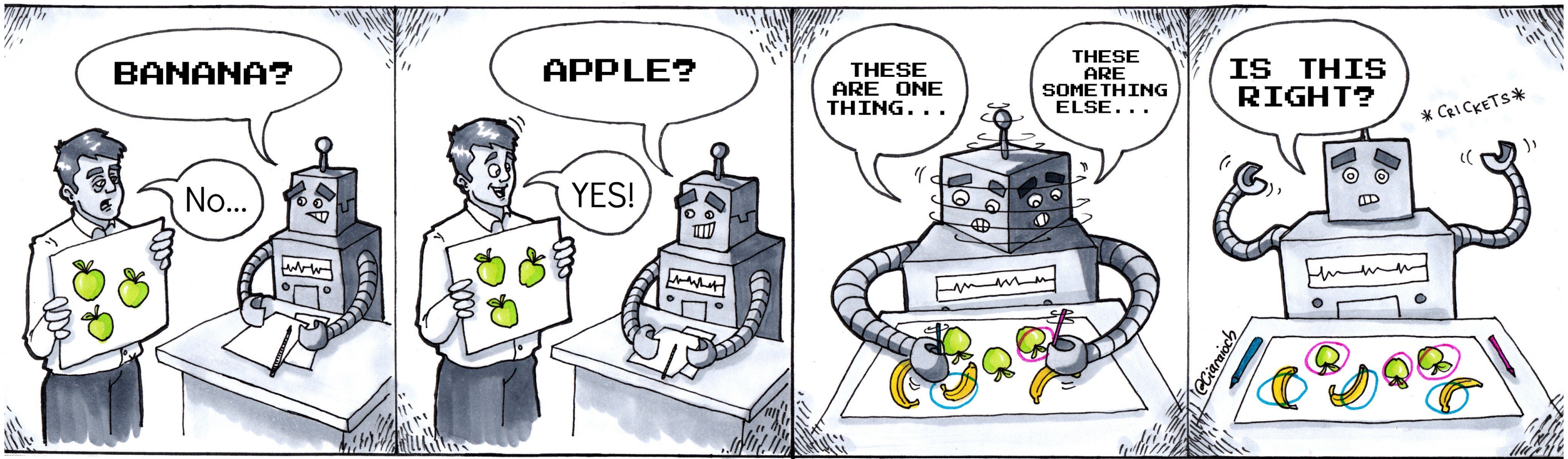
How to learn from data?



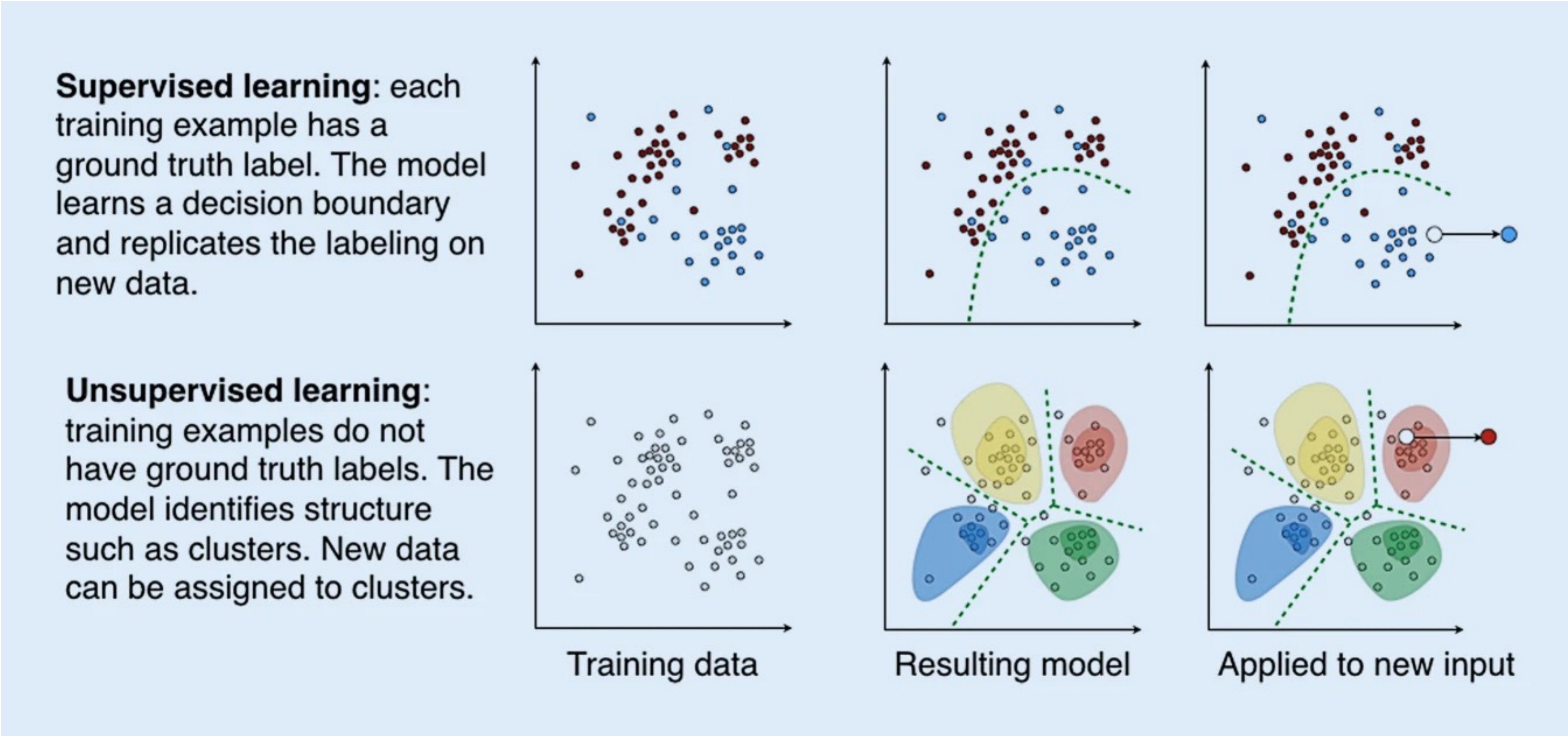
https://clickup.com/blog/wp-content/uploads/2017/08/alternate-machine-learning-image.png

Supervised, unsupervised and semi-supervised

- **Supervised**: algorithm learns on a labeled dataset, providing an answer that the algorithm can use to evaluate its accuracy on training data and further improve the model..
- **Unsupervised**: The algorithm receives unlabeled data and tries to make sense by extracting features, patterns and groups on its own.
- **Semi-supervised learning**: It uses a small amount of labeled data and a larger set of unlabeled data.



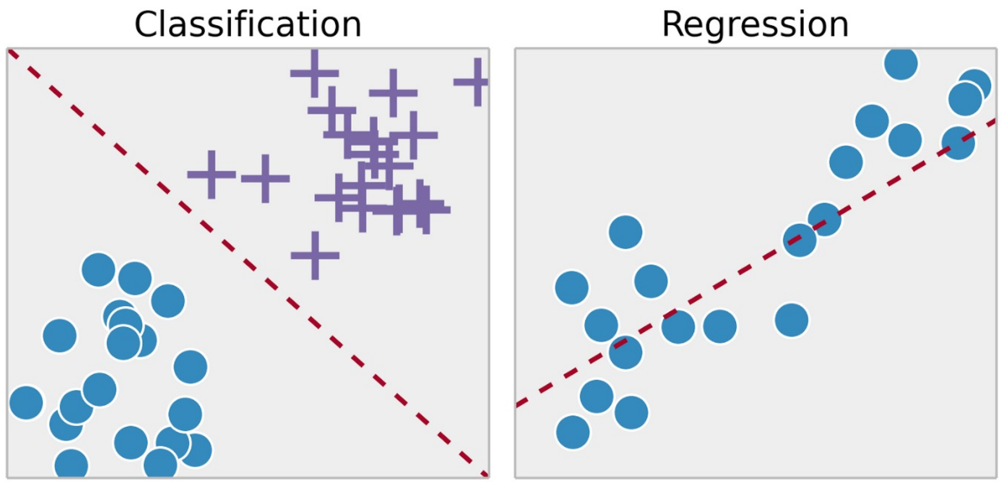
Supervised Learning | Unsupervised Learning



Supervised and unsupervised machine learning,
Attribution: Langs, G., Röhrich, S., Hofmanninger, J. et al., CC BY 4.0 <https://creativecommons.org/licenses/by/4.0>, via Wikimedia Commons

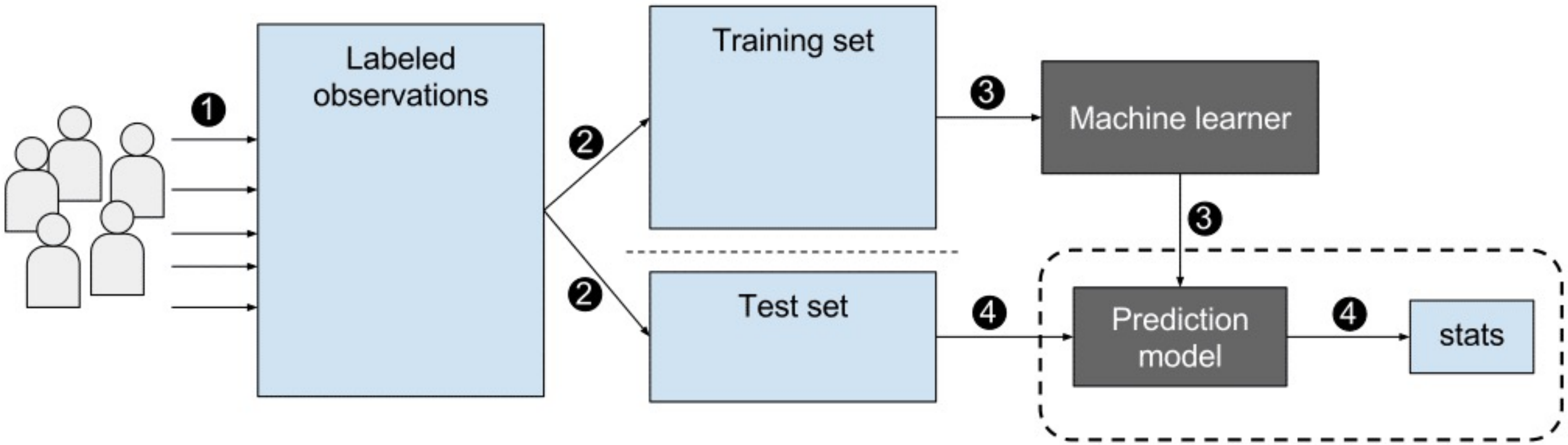
Supervised Learning

- Have access to a training set and a test set. Both have ground truth labels associated with each instance (data-point/image/sample)
- Classification (discrete) or regression (continuous)
- Binary (two classes, two labels)
- Multiclass (>2 classes)
- Multilabel (>1 label pr. instance)



Supervised learning

The algorithm learns on a labeled dataset, providing an answer that the algorithm can use to evaluate its accuracy on the training data, and further improve the model.

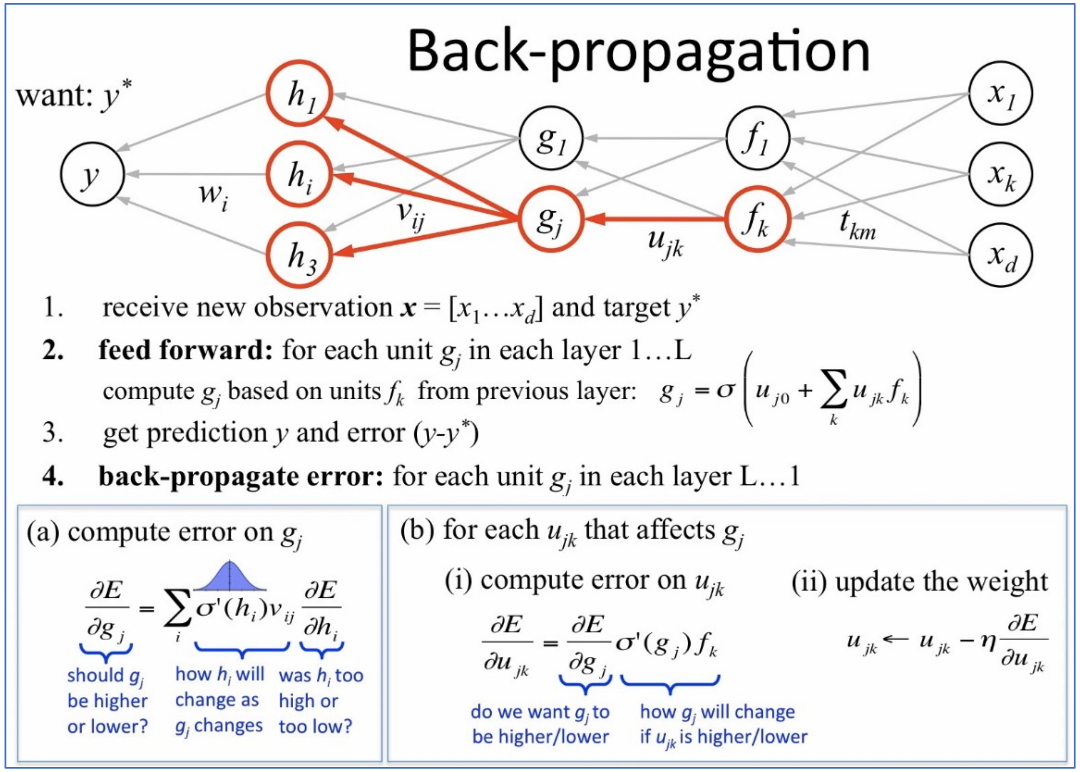


Supervised learning in a nutshell,

Supervised learning – how?

- Loss function
- Feed forward to compute loss
- Backpropagation of the error
- Update weights to reduce error
- Repeated many epochs

(Lectures by Vinay Setty)



attribution: Victor Lavrenko
https://www.youtube.com/watch?v=An5z8lR8asY 6 min. video

Works great – what´s the problem?

Supervised learning is suited to problems where there is a set of available reference points or a ground truth with which to train the algorithm.
Not always the case for different reasons.

- Manual labels are hard to get – expensive work
- There are no way of defining a ground truth that we can label up front

Unsupervised learning

- Access to data, but not to truth-labels. Still much to learn from the data!
- Tasks: Clustering, representation learning, density estimation ..

- Use cases:
  - exploratory analysis – identify structures in data,

  - dimensionality reduction – represent data using less columns/features. Represent our data using latent features (far fewer) interrelating our original features.

- Difficult to compare model performance in many unsupervised learning methods

Unsupervised learning

- Depending on the problem at hand (task), the unsupervised learning model can organize the data in different ways.
  1. Clustering – find natural groups
  2. Anomaly detection – flag outliers
  3. Association – by looking at key attributes, predict other attributes with which they are commonly associated (marketing*; "the customer who bougth this item also bought.."*)
  4. feature learning (dimensionality reduction)– by compression and reconstructing -> autoencoder (For example, learn with both noisy and clean version of an image can use to improve picture quality.)

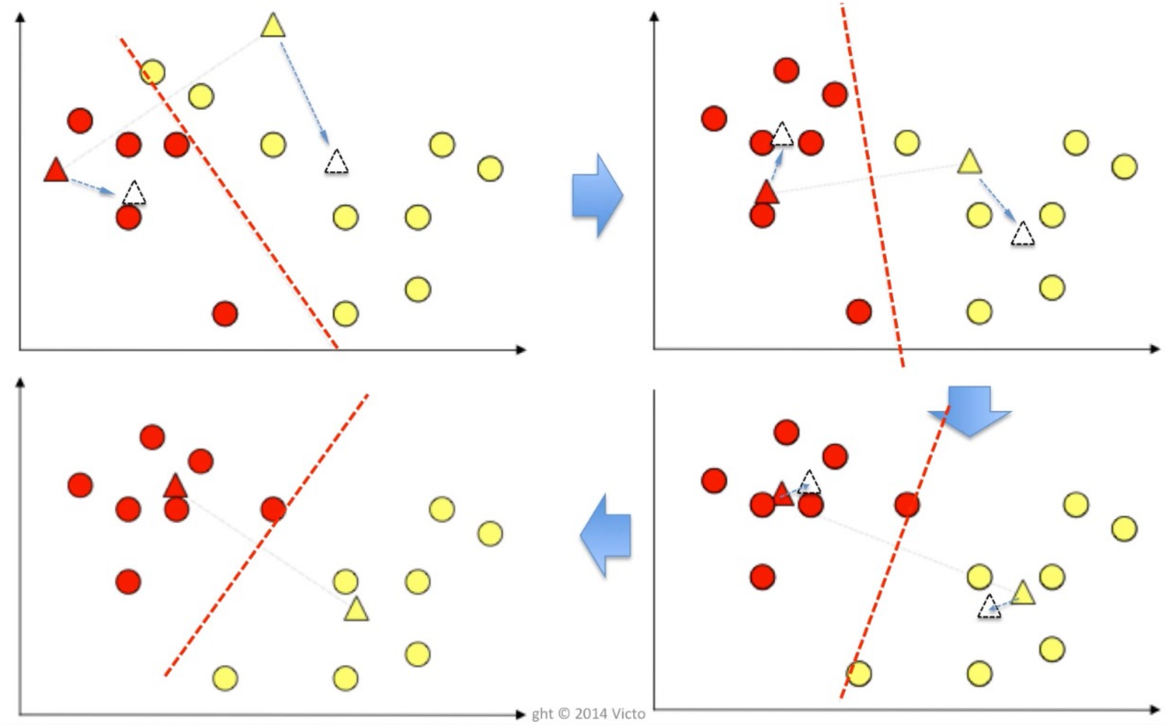
  (Autoencoder is a later topic: Ketil Oppedal)

Unsupervised learning – how?

- Clustering algorithms, for example k-means clustering
- Dimensionality reduction with Principle component analysis (PCA)
- Learning latent feature vectors with Autoencoders (Deep NN, later topic with Ketil Oppedal)
- Deep Belief Networks and Resctricted Boltzman Machine (later topic Kjersti Engan)

K-means clustering

What to cluster?   features



attribution: Victor Lavrenko
https://www.youtube.com/watch?v=IJt62uaZR-M   3,5 min. video

	Supervised Learning	Unsupervised Learning
Discrete	Classification or categorization	Clustering
Continuous	Regression	Dimensionality reduction
Goals	Predict outcomes for new data. You know up front what type of results to expect	Get insight from large volumes of (new) data
Drawbacks	Time-consuming to train. Time consuming or problematic to get access to good labels	Inaccurate results Can be very computationally complex

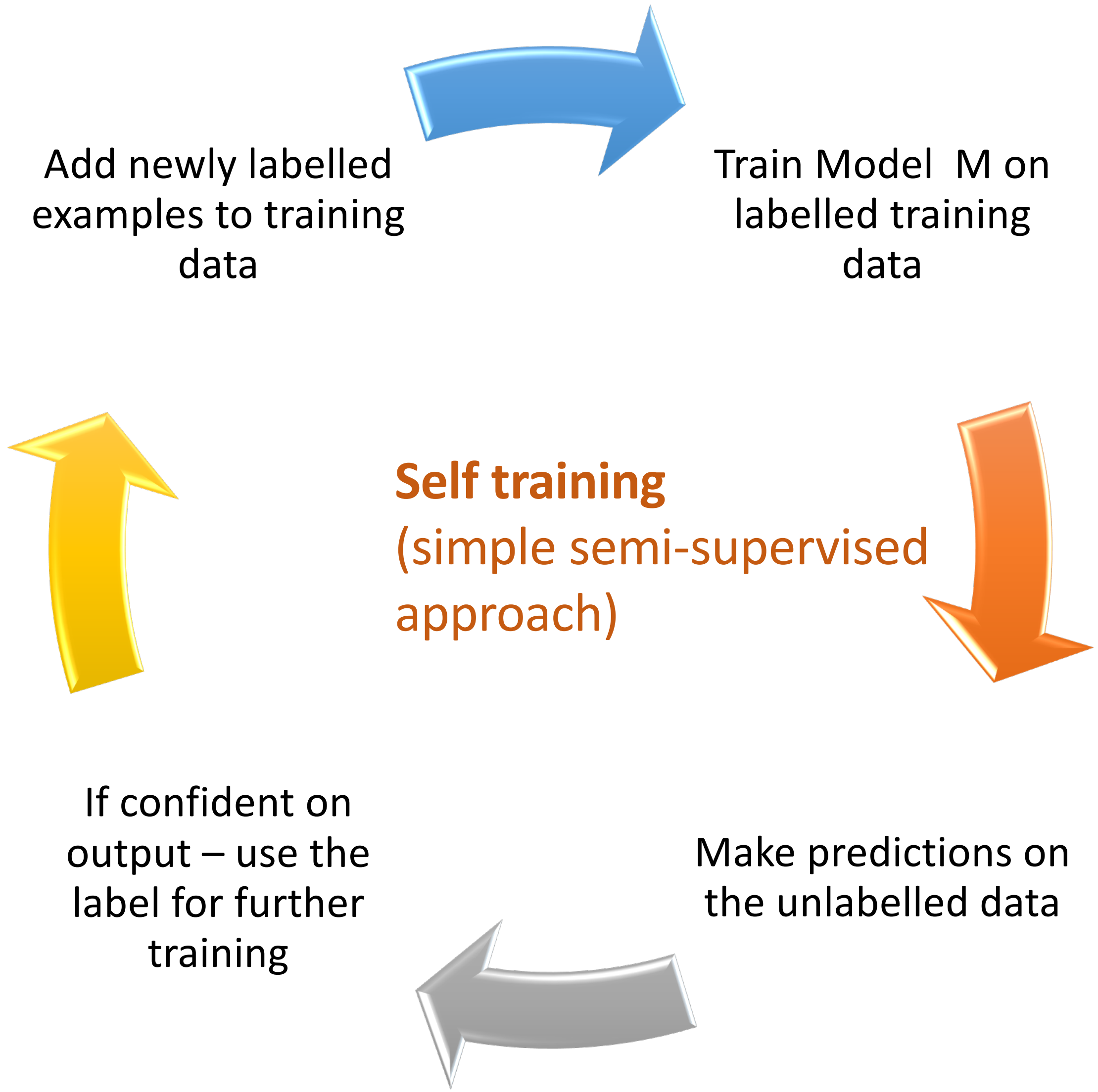
Semi-Supervised learning

- Semi-supervised learning is often used when we have a training dataset with both labeled and unlabeled data.

- Semi-supervised learning algorithms are based on one or more of these assumptions:
  - Smoothness assumption - *Points that are close to each other are more likely to share a label.*

  - Cluster assumption - *The data tend to form discrete clusters, and points in the same cluster are more likely to share a label*

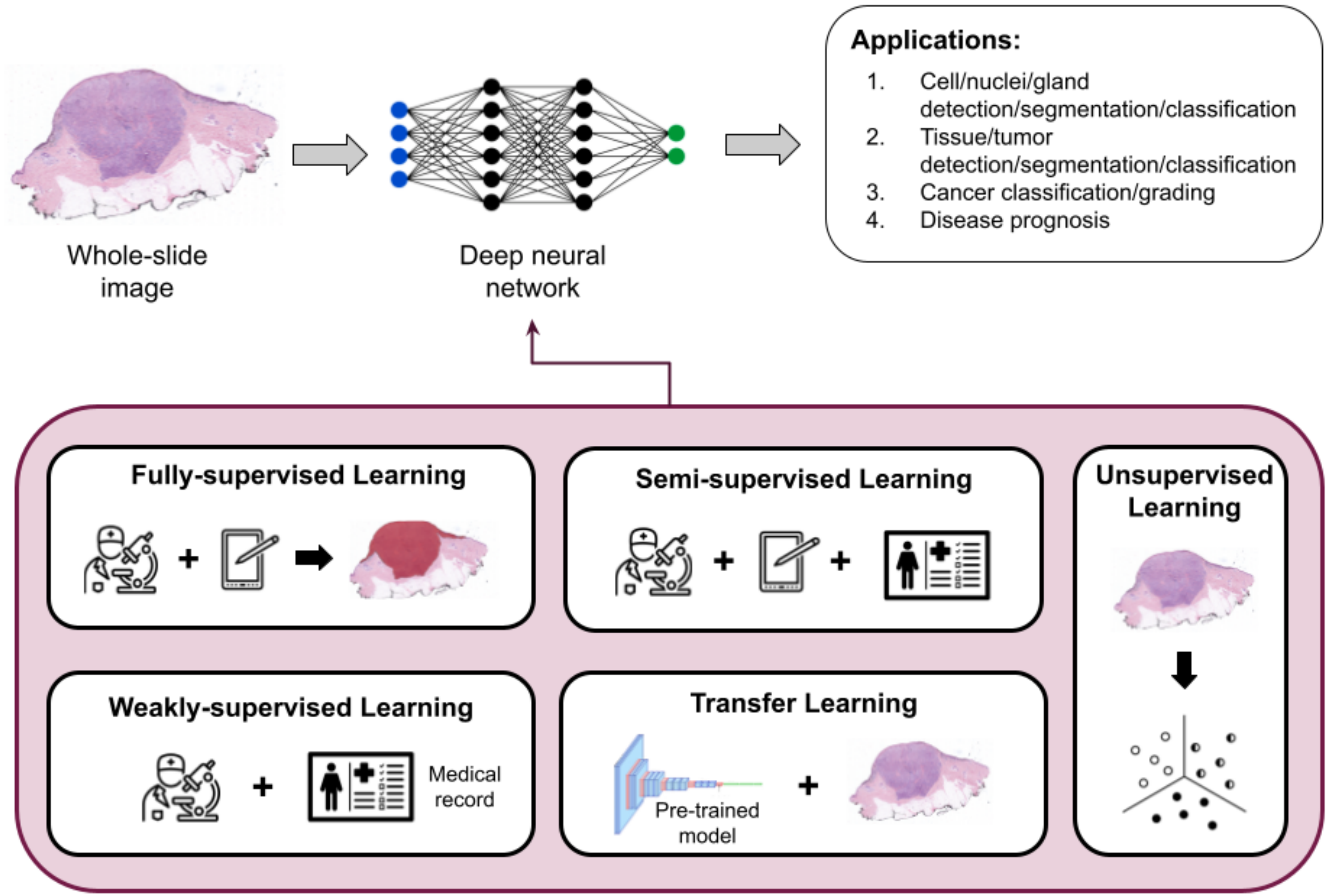
  - Manifold assumption - *The data lie approximately on a manifold of much lower dimension than the input space.*



Do we really learn anything new? We only use what we are already confident on

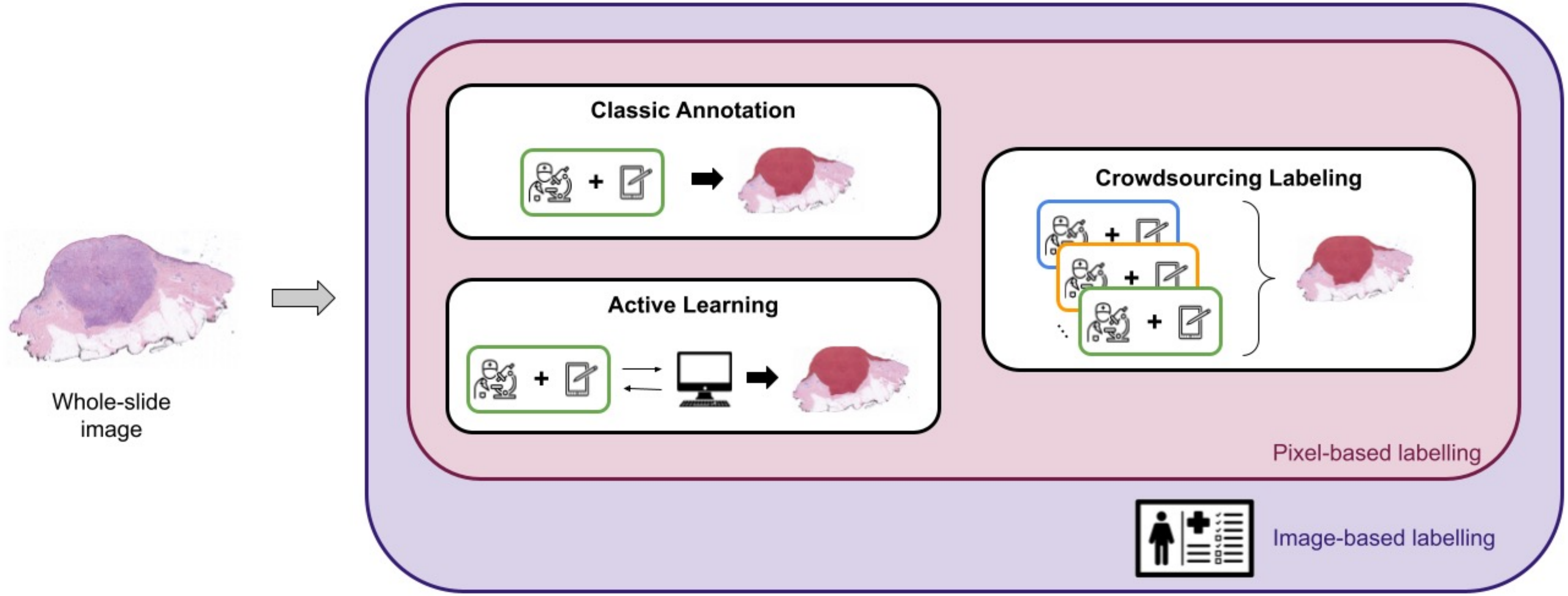
Cluster assumption

- When assumptions do not hold ? We might performe worse after updates.
- other approach: link estimated parameters (mean, variance etc.) of labeled samples to those of all available samples.



Learning schemes – example from computational pathology

Attribute: Morales, Sandra, Kjersti Engan, and Valery Naranjo. "Artificial intelligence in computational pathology—challenges and future directions." Digital Signal Processing (2021): 103196.

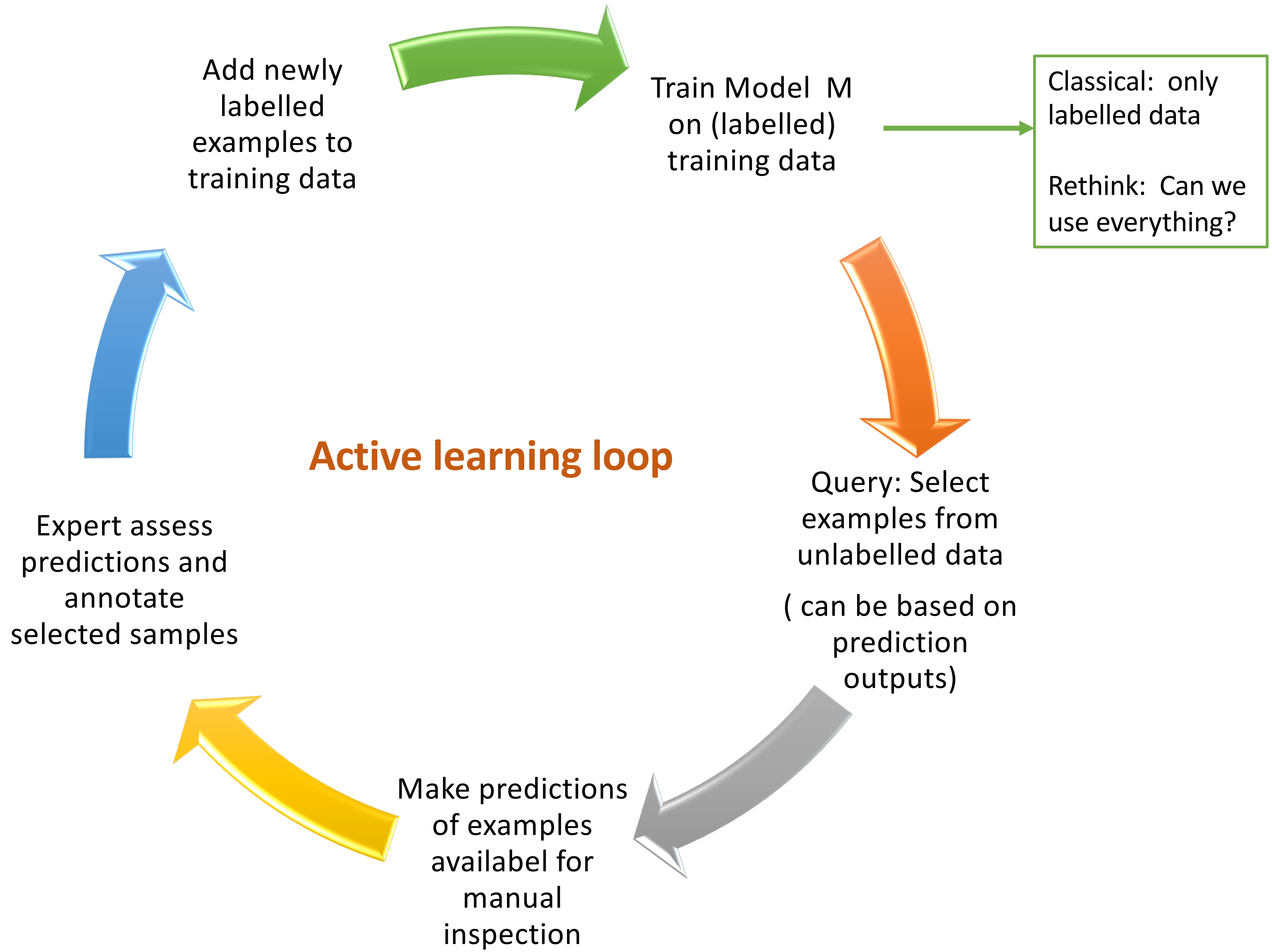


Labelling approaches in computational pathology

Attribute: Morales, Sandra, Kjersti Engan, and Valery Naranjo. "Artificial intelligence in computational pathology—challenges and future directions." Digital Signal Processing (2021): 103196.

Active and assistant learning

- Active or assisted learning is also called “human-in-the-loop” learning.
- Main idea: We do not have enough resources to label all the data prior to learning. Lets start with a small set, and take advantage of the model as we go.
- Label a small set A
- Supervised learning with A -> produce model, M1
- M1 used to predict unlabelled set B. The outputs are manually assessed, and sorted (right/wrong). The model is further learned on set B (and A).


Add newly labelled examples to training data
Train Model M on (labelled) training data
Classical: only labelled data
Rethink: Can we use everything?
Active learning loop
Query: Select examples from unlabelled data
(can be based on prediction outputs)
Make predictions of examples availabel for manual inspection
Expert assess predictions and annotate selected samples

Transfer learning

Transfer Learning is a machine learning method where we apply a pre-trained model as a starting point for developing another model for a similar task.

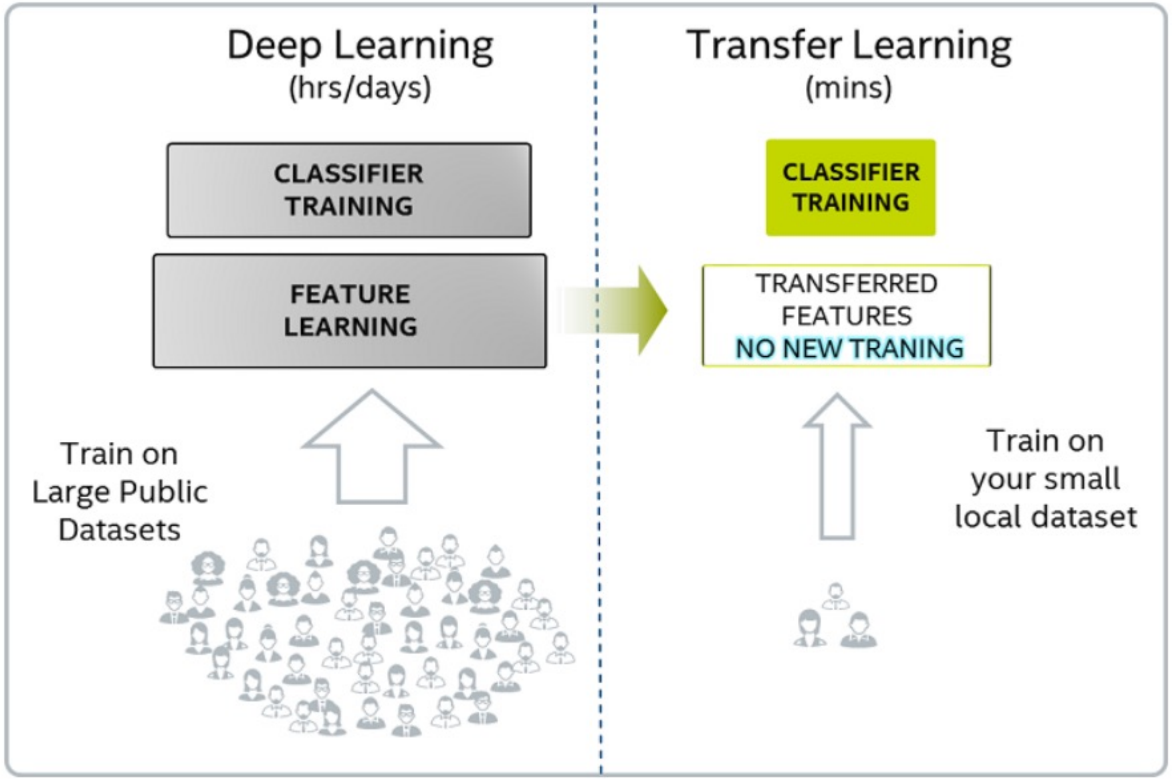


image src = MLconf/Transfer learning
https://ai.plainenglish.io/transfer-learning-a-shortcut-for-training-deep-learning-models-fe32c2ac4df1

Transfer learning

«This is typically understood in a supervised learning context, where the input is the same but the target may be of a different nature. For example, we may learn about one set of visual categories, such as cats and dogs, in the first setting, then learn about a different set of visual categories, such as ants and wasps, in the second setting.»
— Page 536, Y.Bengio et.al. Deep Learning, 2016.

«… the objective is to take advantage of data from the first setting to extract information that may be useful when learning or even when directly making predictions in the second setting.»

— Page 538, Y.Bengio et.al. Deep Learning, 2016.

TABLE 2
Different Settings of Transfer Learning

Transfer Learning Settings	Related Areas	Source Domain Labels	Target Domain Labels	Tasks
Inductive Transfer Learning	Multi-task Learning	Available	Available	Regression, Classification
	Self-taught Learning	Unavailable	Available	Regression, Classification
Transductive Transfer Learning	Domain Adaptation, Sample Selection Bias, Co-variate Shift	Available	Unavailable	Regression, Classification
Unsupervised Transfer Learning		Unavailable	Unavailable	Clustering, Dimensionality Reduction

From : Pan, Sinno Jialin, and Qiang Yang. "A survey on transfer learning." *IEEE Transactions on knowledge and data engineering* 22.10 (2009): 1345-1359 , https://www.cse.ust.hk/~qyang/Docs/2009/tkde_transfer_learning.pdf

Transfer learning – when and why?

- **Higher start**. The initial performanvce is higher than it otherwise would be.
- **Higher slope**. The rate of improvement of the model during the training is steeper than it otherwise would be.
- **Higher asymptote**. The converged skill of the trained model is better than it otherwise would be.

- **Large dataset for a similar task.** We do not have enough data to learn our network from scratch

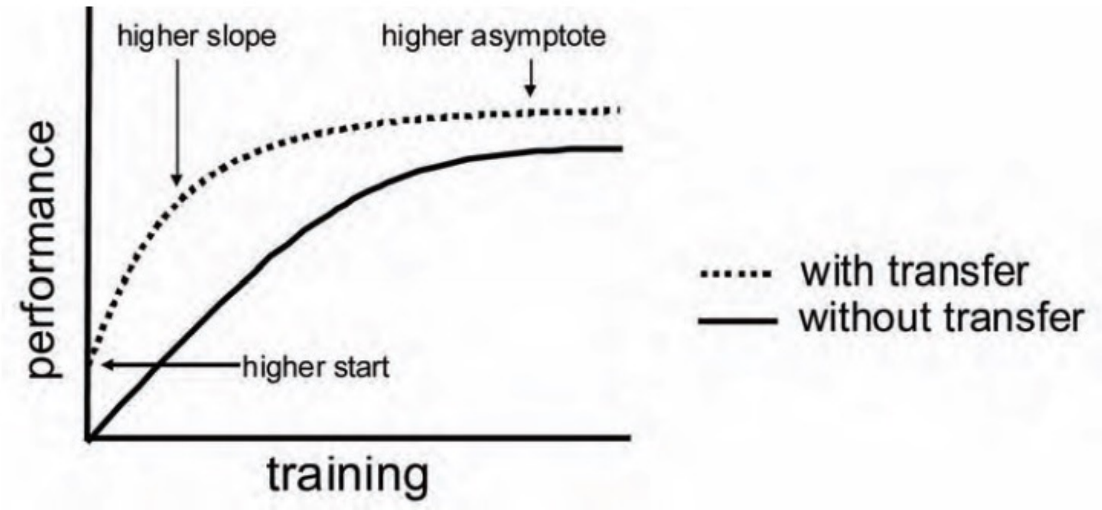
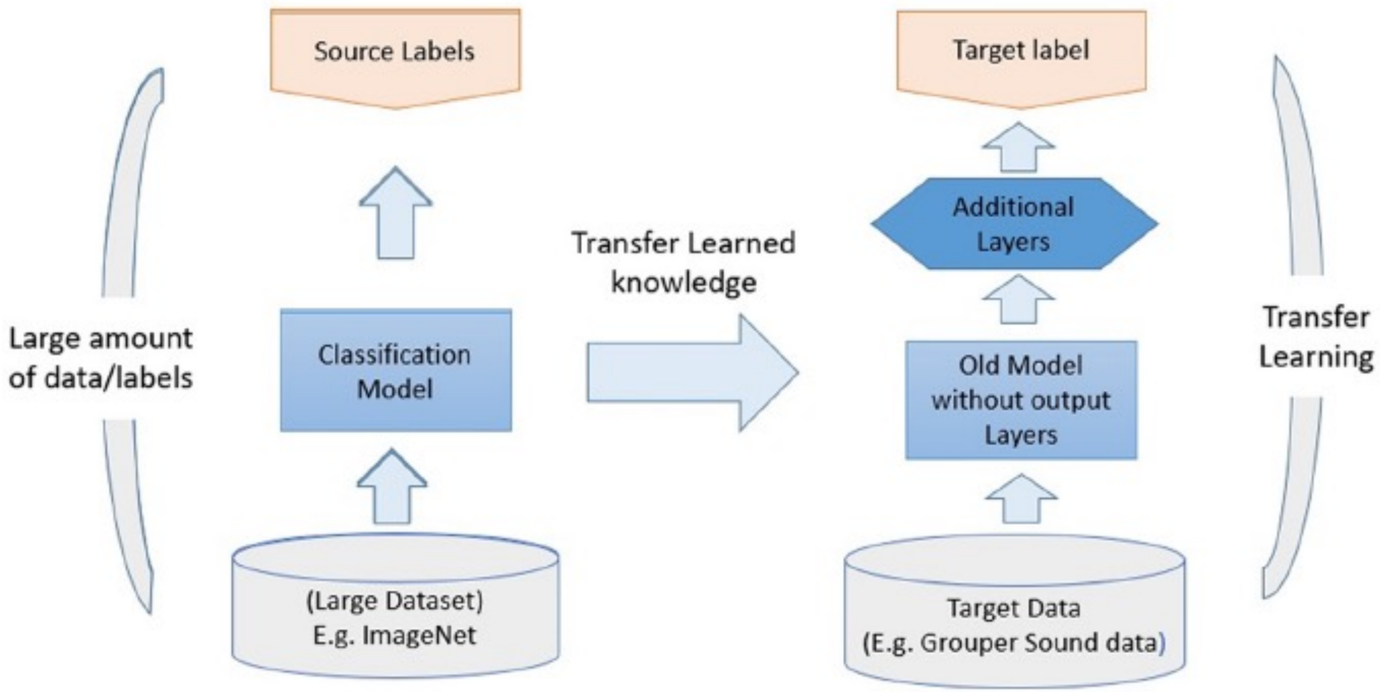


image src = Handbook of Research on Machine Learning Applications and Trends Algorithms, Methods, and Techniques by Emilio Soria Olivas
https://ai.plainenglish.io/transfer-learning-a-shortcut-for-training-deep-learning-models-fe32c2ac4df1

Often used models learned on ImageNet for differfent image processing or computer vision tasks, ex. VGG16 /VGG19

Weights inpretrained network can be **frozen or unfrozen**, or partly unfrozen.



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Upcoming and related topics in ELE 680

- A popular training method that starts with a fairly small set of labeled data is using General Adversarial Networks, or GAN (Separate lecture by Ketil Oppedal).
- Autoencoders (Ketil Oppedal)
- Strong and weak labels (K.Engan)

References and further reading

- I.Goodfellow, Y.Bengio, A. Courville «Deep Learning», book
- Cheplygina, Veronika, Marleen de Bruijne, and Josien PW Pluim. "Not-so-supervised: a survey of semi-supervised, multi-instance, and transfer learning in medical image analysis." *Medical image analysis* 54 (2019): 280-296. https://www.sciencedirect.com/science/article/pii/S1361841518307588
- Y.Bengio et.al. «Representation Learning: A Review and New Perspectives» https://arxiv.org/pdf/1206.5538.pdf
- S. Morales, K. Engan, and V. Naranjo. "Artificial intelligence in computational pathology–challenges and future directions." Digital Signal Processing (2021) https://www-sciencedirect-com.ezproxy.uis.no/science/article/pii/S1051200421002359
- https://towardsdatascience.com/supervised-vs-unsupervised-learning-14f68e32ea8d
- https://blogs.nvidia.com/blog/2018/08/02/supervised-unsupervised-learning/
- P. Ren et.al. "A Survey of deep active learning", arXiv:2009.00236
- https://machinelearningmastery.com/how-to-use-transfer-learning-when-developing-convolutional-neural-network-models/
- https://towardsdatascience.com/transfer-learning-with-convolutional-neural-networks-in-pytorch-dd09190245ce
- https://ai.plainenglish.io/transfer-learning-a-shortcut-for-training-deep-learning-models-fe32c2ac4df1
- Pan, Sinno Jialin, and Qiang Yang. "A survey on transfer learning." *IEEE Transactions on knowledge and data engineering* 22.10 (2009): 1345-1359 , https://www.cse.ust.hk/~qyang/Docs/2009/tkde_transfer_learning.pdf