OTH
Amberg-Weiden

Advanced Topics in Machine Learning

Winter Semester 2024/2025

Prof. Dr.-Ing. Christian Bergler | OTH Amberg-Weiden

Advanced Topics in Machine Learning

Overview

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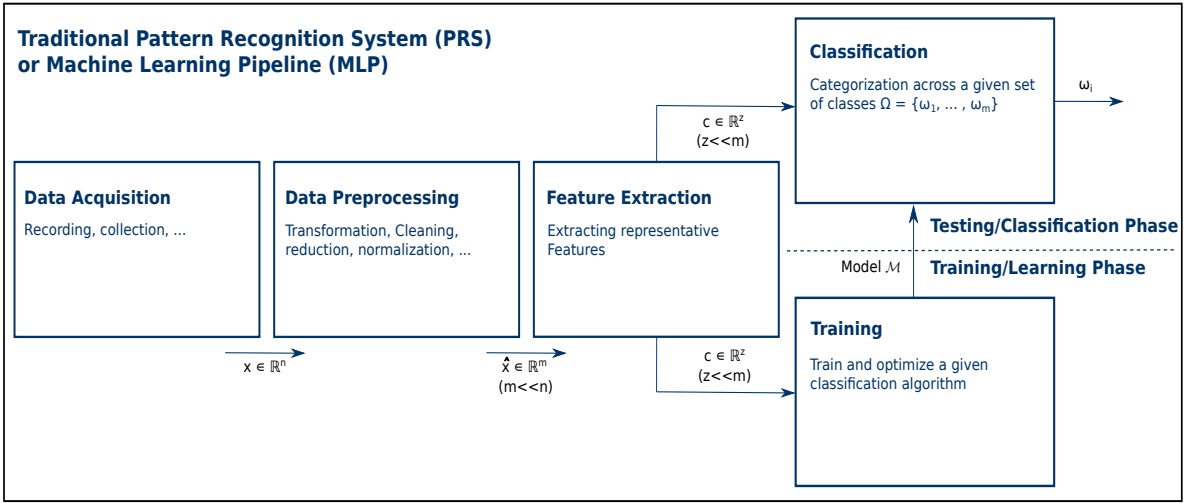
Topics From Last Time: Introduction & Deep Learning Recap

- Signals and Signal Types
- Audio Signals in Deep Learning
- Analog/Digital (A/D) Conversion (Sampling, Quantization)
- Discrete Fourier Transform (DFT)
- Short-Time Fourier Transform (STFT)
- Spectrogram
- Multimodal Learning

Topics of Today: Advanced Deep Learning Strategies – Part I

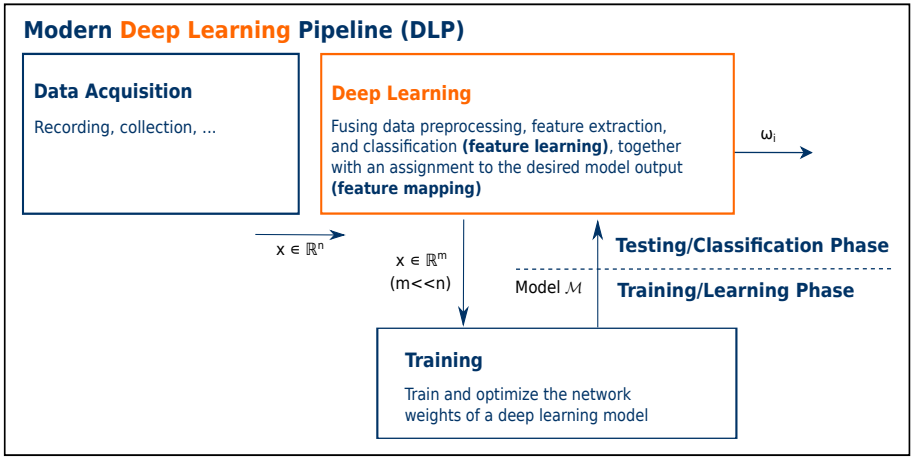
- Representation Learning
- Transfer Learning
- Distillation Learning
- Deep Metric Learning (Focus: Contrastive Learning)



Source: Image from Christian Bergler, Dissertation "Deep Learning Applied To Animal Linguistics", 2023

Depp Learning

Deep Learning Pipeline



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Terminology

Feature Extraction & Feature Selection VS. Feature/Representation Learning

Feature Extraction/Engineering

- Building a new feature subspace $c \in \mathbb{R}^n$, derived from information of the original features $f \in \mathbb{R}^m$ (usually $n << m$) to create enhanced representations for model interpretation and improvement

  $\rightarrow$ Feature transformation and (often) dimensionality reduction

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Feature/Representation Learning

- Fully data-driven and automatic procedure to learn and discover the most important (unknown) underlying data characteristics (features) by transforming and reducing input

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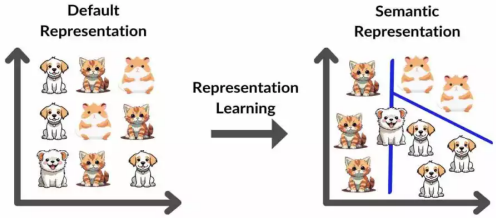
Why we want to Learn Feature Representations?

- Discover the underlying patterns and features in raw data
- Learn informative, (often) compressed, and hierarchical representations that capture the essential characteristics



Source: Image from https://spotintelligence.com/2023/12/11/representation-learning/

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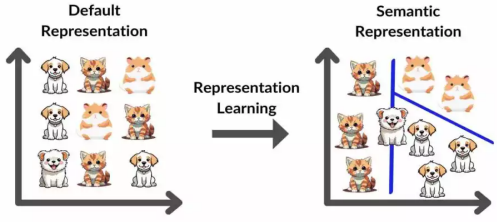

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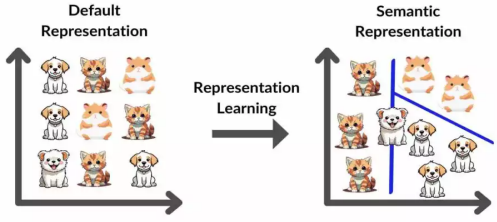
- Discover the underlying patterns and features in raw data
- Learn informative, (often) compressed, and hierarchical representations that capture the essential characteristics
- Better performance on downstream tasks like classification, regression, and clustering
- Representation learning combines feature extraction/selection, dimensionality reduction and results in a better overall generalization

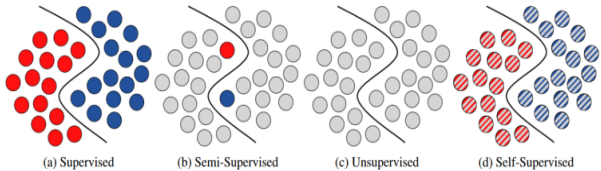


→ How about Training data?

Source: Image from https://spotintelligence.com/2023/12/11/representation-learning/

Different Ways of Representation Learning

- Supervised: representations optimized for a specific task using labeled data (e.g. CNNs)



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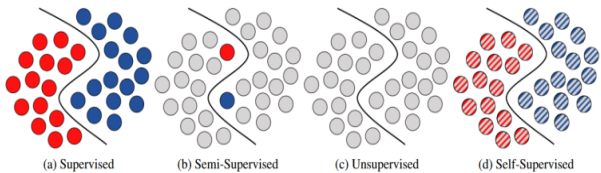

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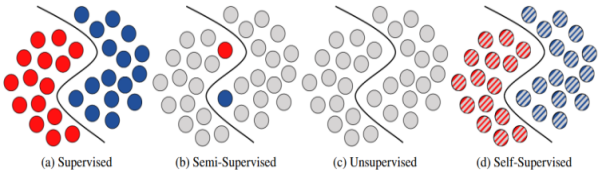

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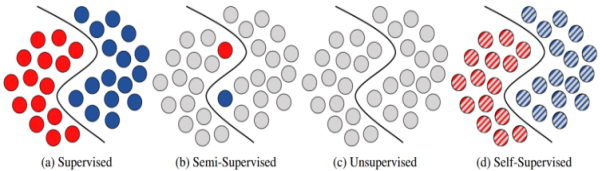
- Self-Supervised: type of unsupervised learning using its own ("pseudo") labels from the unlabeled data corpus to predict missing parts & build different views of a single object
- Semi-Supervised: small amount of labeled data with a larger pool of unlabeled data to learn representations (self-supervised/unsupervised pre-training with supervised fine-tuning)



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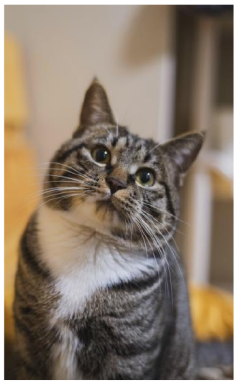
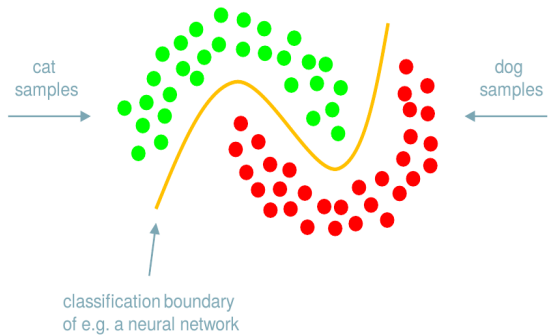
Deep Learning Paradigms – Part I

Representation Learning

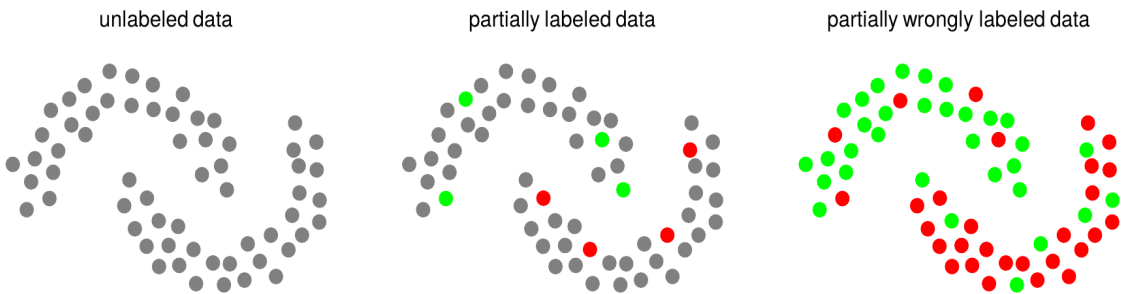
Purely Supervised!





Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Reality!

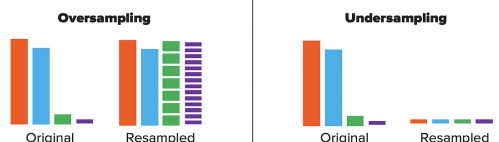


- Unlabeled data (unsupervised, self-supervised), partial labeled (semi-supervised), labeled, but partially wrong (weakly supervised)

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Careful! Data Imbalance?

- Data Imbalance: classes/categories in a dataset have significantly fewer examples (minority class) than others (majority class) resulting in a biased model



Source: Image from https://towardsdatascience.com/4-ways-to-improve-class-imbalance-for-image-data-9adec8f390f1

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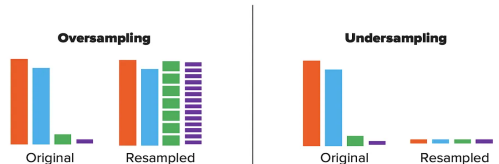
- Countermeasures: collect/label more data of the minority class, reduce number of samples in majority class (undersampling!), increase number of samples in minority class (oversampling!)



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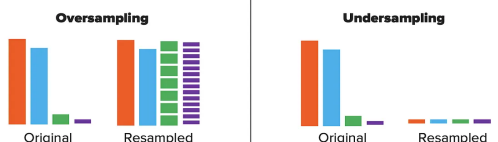
- Countermeasures: collect/label more data of the minority class, reduce number of samples in majority class (undersampling!), increase number of samples in minority class (oversampling!)
- Techniques: Undersampling – random deletion, condensed nearest-neighbor (NN), edited NN, tomek links; Oversampling – random copy, SMOTE (Synthetic Minority Oversampling Technique)



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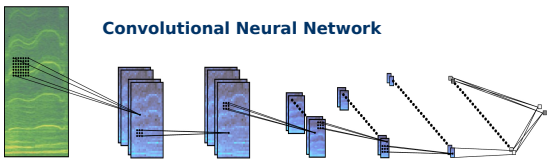
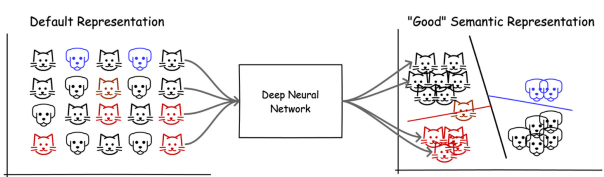
Convolutional Neural Network

Supervised representation learning using a CNN, which consists of the following fundamental types of layers (others are of course possible):

- Convolution, normalization, activation layers for feature extraction
- Pooling layers for downsampling
- Fully Connected Layers for classification (e.g. softmax activation at the output layer)

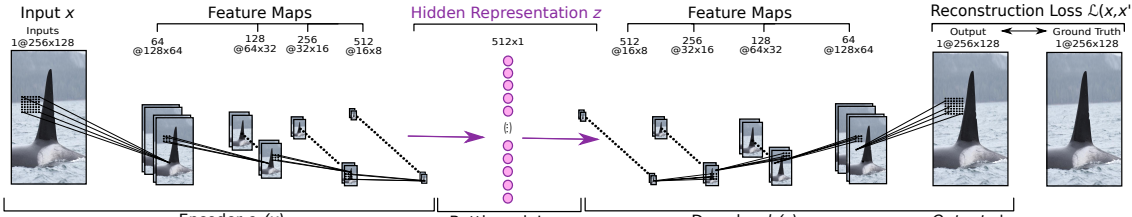




(Purely Data-Driven) Feature Learning and Classification (End-to-End)

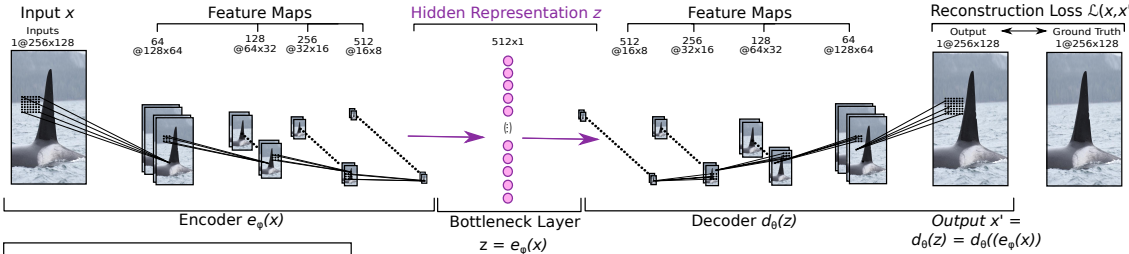
Source: OTH-AW, Electrical Engineering, Media and Computer Science, Fabian Brunner – Vorlesung Convolutional Neural Networks

Autoencoder – General Architecture and Concept



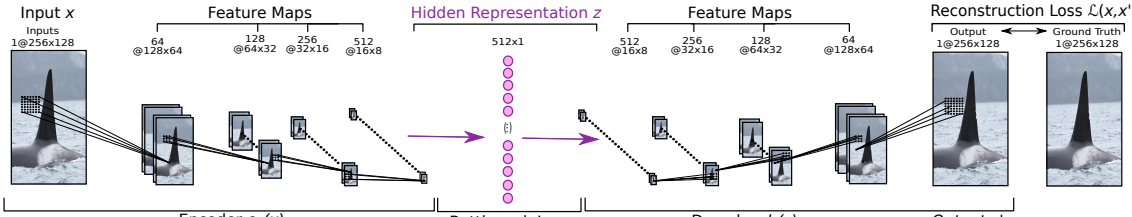
- Mapping a given input x to an output/reconstruction x' via a hidden representation z (deterministic!)

Autoencoder – General Architecture and Concept



- Mapping a given input x to an output/reconstruction x' via a hidden representation z (deterministic!)
- Encoder e_φ, acting as a function to map (encode) the input x to the hidden representation z via $e_\varphi(x)$

Autoencoder – General Architecture and Concept



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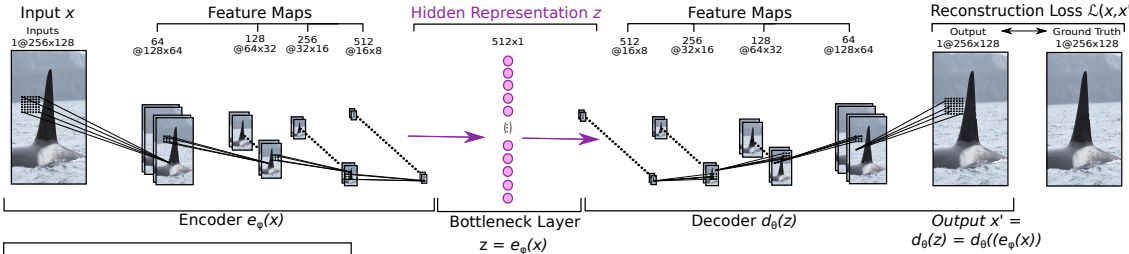
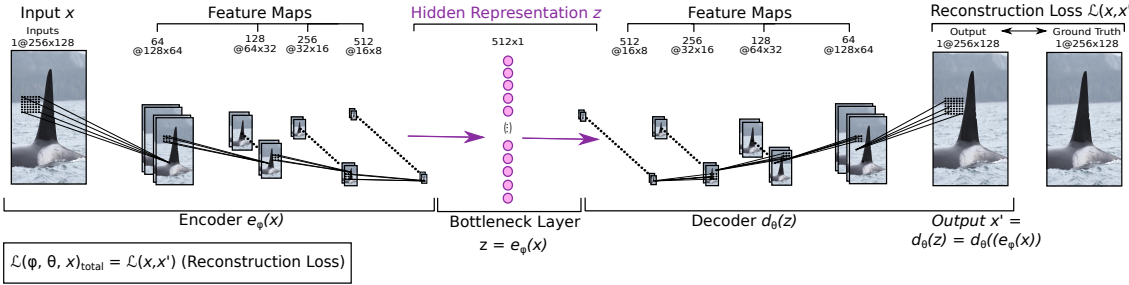
- Decoder d_θ, acting as a function to map (decode) the hidden latent code z to the

Autoencoder – General Architecture and Concept



- General Idea: Learn an embedding z (latent code) including the most prominent features by minimizing the reconstruction loss $L(x, d_\theta(e_\varphi(x)))$, penalizing the dissimilarity between x and $d_\theta(e_\varphi(x))$ (e.g. squared L_2-norm)

Autoencoder – General Architecture and Concept



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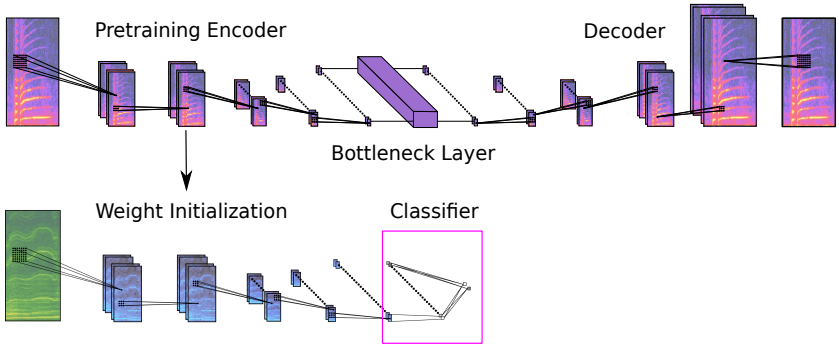
- Data compression as well as data transformation (feature extraction/engineering) is done automatically

Deep Learning Paradigms – Part I

Semi-Supervised Representation Learning – Handling Unlabeled Data?

Combination of Supervised & Unsupervised Representation Learning (CNN + AE)



- Unlabelled data is used for pretraining (representation learning, transfer learning), whereas the learned weights are used as initialization and are further optimized using the (smaller) labelled data in a downstream supervised approach (fine-tuning)

Source: Images from Christian Bergler, Dissertation "Deep Learning Applied To Animal Linguistics", 2023

Deep Learning Paradigms – Part I

Transfer Learning

- Focus: transfering knowledge from a given source domain D_s and task T_s, to a different target domain D_t and task T_t
- Inspired by the ability of humans to transfer expertise across domains

Source: https://www.linkedin.com/pulse/traditional-training-vs-transfer-learning-based-enjoyalgorithms

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- Source domain: $D_s = \{X, P(X)\}$ with $X = \{x_1, ..., x_n\}$ as the sample-specific feature vectors in the entire dataset and $P(X)$ as the marginal distribution

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- Source task: $T_s = \{Y, f(\cdot)\} = \{Y, P(Y|X)\}$ with label space $Y = \{y_1, ..., y_k\}$ together with a learnable decision function (Deep Learning Model) $f(\cdot)$

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classification task

- Source task: $T_s = \{Y, f(\cdot)\} = \{Y, P(Y|X)\}$ with label space $Y = \{y_1, ..., y_k\}$ together with a learnable decision function (Deep Learning Model) $f(\cdot)$
- $f(\cdot)$ trained on pairs of feature vectors $x_j \in X$ & associated label $y_i \in Y$, with $f(x_j) = y_i$
- Transfer learning addresses a DL-strategy, aiming to enhance the model performance of $f(\cdot)$ within D_t w.r.t. task T_t, by leveraging knowledge from $f(\cdot)$ in D_s w.r.t. task T_s, while $D_s \neq D_t$ or $T_s \neq T_t$

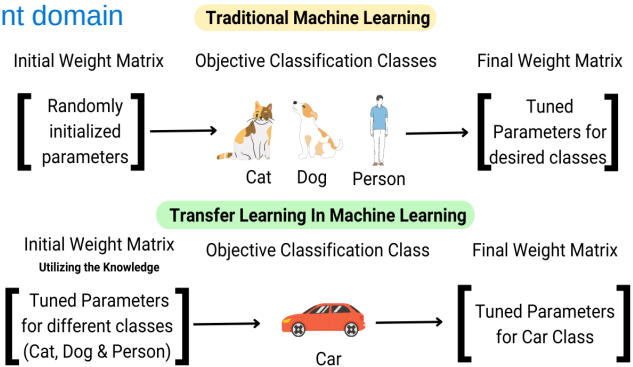
Source: https://www.linkedin.com/pulse/traditional-training-vs-transfer-learning-based-enjoyalgorithms

Deep Learning Paradigms – Part I

Transfer Learning

- Goal: Transferring knowledge of large-scale (labeled/unlabeled) data in domain D_s and task T_s, to handle a similar and related task T_t, traditionally with a significantly lower amount of (labeled or unlabeled) data in domain D_t

same task but diffferent domain



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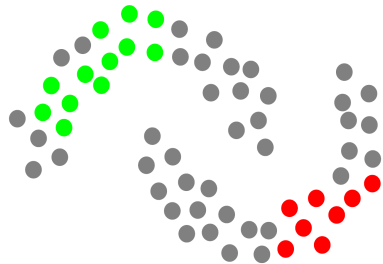
Deep Learning Paradigms – Part I

Semi-Supervised Representation Learning – Handling Unlabeled Data?



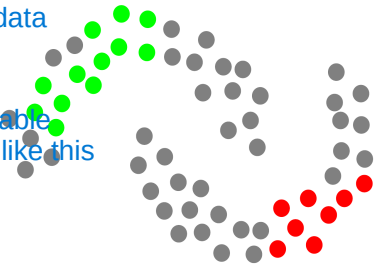
- Smoothness Assumption: If two samples are similar or close to each other, their labels should also be similar or close

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Deep Learning Paradigms – Part I

Semi-Supervised Representation Learning – Handling Unlabeled Data?

here we still need a labeled data



the classifier should be trustable
i.e the propbabilti should be like this
0.9
0.05
0.05
not like this
0.6
0.3
0.1

- Smoothness Assumption: If two samples are similar or close to each other, their labels should also be similar or close
- Use partially labeled data to train a classifier on both labeled and unlabeled data →
  Idea: propagating labels from labeled samples to unlabeled samples

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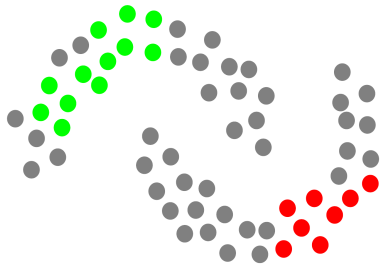


- Smoothness Assumption: If two samples are similar or close to each other, their labels should also be similar or close
- Use partially labeled data to train a classifier on both labeled and unlabeled data → Idea: propagating labels from labeled samples to unlabeled samples
- Approaches: Pseudo Labeling & Consistency Regularization

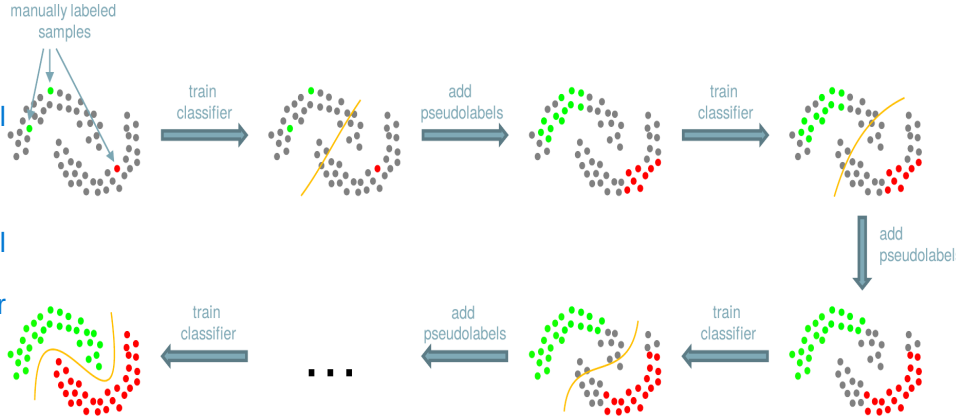
Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Deep Learning Paradigms – Part I

Semi-Supervised Representation Learning – Handling Unlabeled Data?

Pseudo Labeling

when sure
assign the label
and then train
classifier and
then abgain
check and label
and thr again
train a classifier

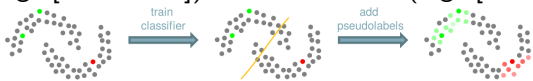


- Iterative Procedure: a) train initial classifier with existing labels, b) predict unknowns, c) assign pseudo-labels to samples with high confidence, d) re-train, e) repeat b–c)

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Pseudo Labeling – Ways to Improve!

- Confidence Thresholding: only incorporate pseudo-labels for training in case the prediction is above a given threshold δ
- Soft labels (softmax, e.g. [0, 0.3, 0.7]) VS. hard labels (e.g. [0, 0, 1]) for pseudo labels



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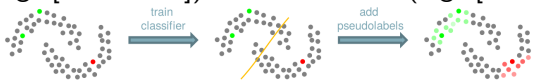

- Label Refinement: refine pseudo-labels over time by re-evaluating them after each training iteration or epoch

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

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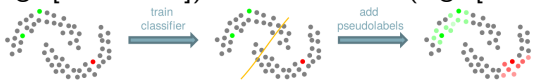

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- Ensemble Learning: incorporate boosting or bagging

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Semi-Supervised Representation Learning – Handling Unlabeled Data?

last model will do sudo label again to all the labels

Pseudo Labeling – Ways to Improve!

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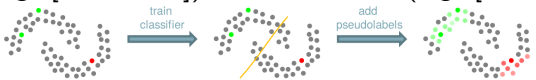
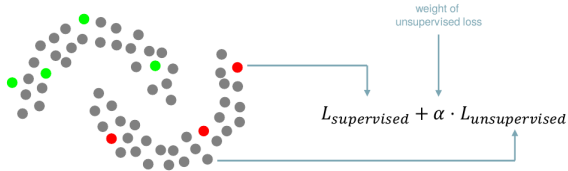


- Label Refinement: refine pseudo-labels over time by re-evaluating them after each training iteration or epoch
- Ensemble Learning: incorporate boosting or bagging
- Co-Training: optimizing the model on multiple "representations" (views) at each step (feature split, PCA, ...)

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

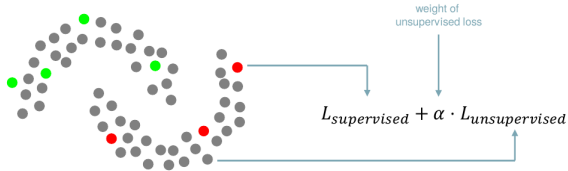
Consistency Regularization



- Idea: use a bipartite loss as a combination between the supervised loss L_{sup} and unsupervised loss L_{unsup}

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Consistency Regularization



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- Recap "Smoothness": unsupervised loss ensures that close samples, lead to close predictions, while the supervised loss ensures the predictions to be correct

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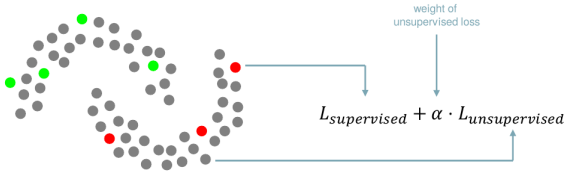
Consistency Regularization



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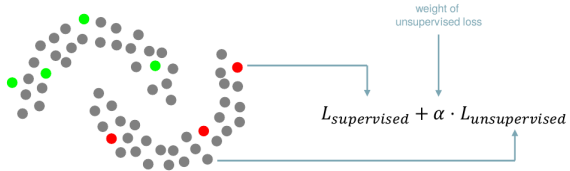

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Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Deep Learning Paradigms – Part I

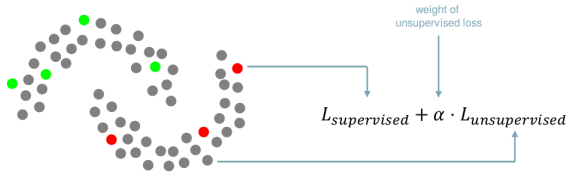
Semi-Supervised Representation Learning – Handling Unlabeled Data?

OTH Amberg-Weiden

weighting loss

mean square error is a loss for unsupervised loss

Consistency Regularization



alpha is decided bsaed on the number of lablebes data points we have

- Idea: use a bipartite loss as a combination between the supervised loss L_{sup} and unsupervised loss L_{unsup}
- Recap "Smoothness": unsupervised loss ensures that close samples, lead to close predictions, while the supervised loss ensures the predictions to be correct
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- If α is large, the model relies more on consistency for unlabeled data, and if small, the focus is more on the labeled data
- Using the unlabeled data to reinforce the model's learning

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Deep Learning Paradigms – Part I

Semi-Supervised Representation Learning – Handling Unlabeled Data?

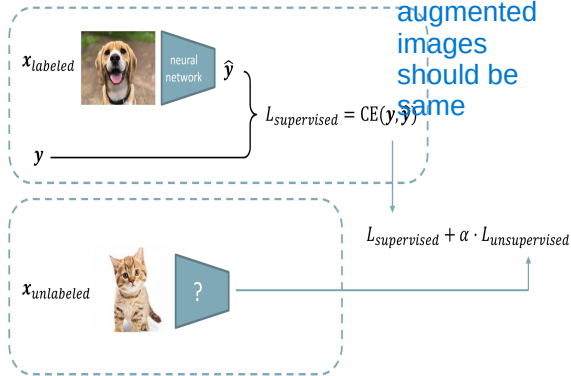
Consistency Regularization – General Approach

1. Input: take an unlabeled input sample x
2. Augmentation/Perturbation: create a number of n versions of this sample $\tilde{x}^1, \tilde{x}^2$ (rotation, scaling, noise)
3. Prediction: n predictions $f(\tilde{x}^1)$ & $f(\tilde{x}^2)$
4. Consistency Loss: difference between these two predictions (e.g. MSE-Loss), penalizing the model if its predictions for the two perturbed images are not similar

→ Minimizing consistency loss w.r.t. unlabeled data, thus being invariant to small changes?

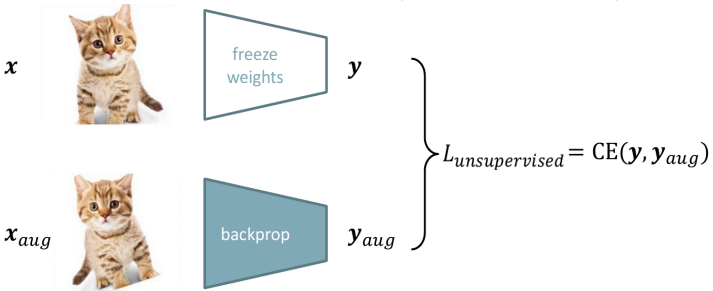
intresting

do augmentation the predcition for both the augmented images should be same



Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Consistency Regularization – Data Augmentation (Rotation, Scaling)

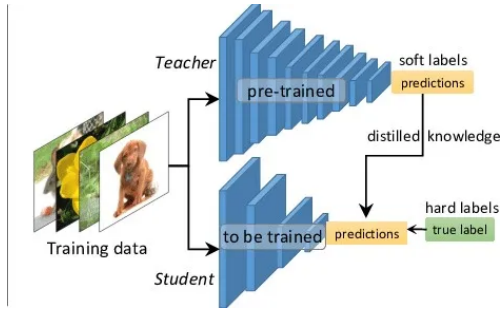


- Computing the unsupervised loss L_{unsup} by comparing the model prediction $y = f(x)$ with the model prediction using the augmented input $y_{aug} = f(x_{aug})$
- Similar samples x_{aug} are computed via various Augmentation techniques
- Different learning concepts following the "Student-Teacher" Learning Approach

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Different Concepts (Student-Teacher)

1. Frozen Teacher:
   - Teacher weights are frozen during training
   - Robust pre-trained teacher model required



Source: Image from https://towardsdatascience.com/knowledge-distillation-simplified-dd4973dbc764

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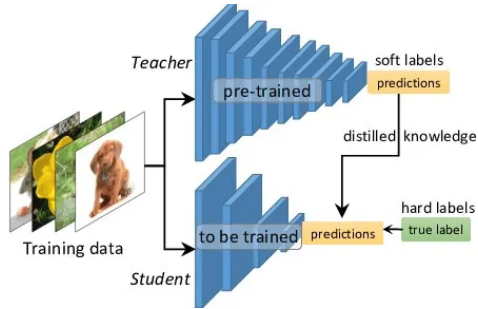
   - Teacher's weights are updated as EMA of the student's weights (smoothed version), allowing the teacher to gradually capture improvements



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OTH Amberg-Weiden

try to distilate fr a knowledge from tracher to student

Different Concepts (Student-Teacher)

1. Frozen Teacher:
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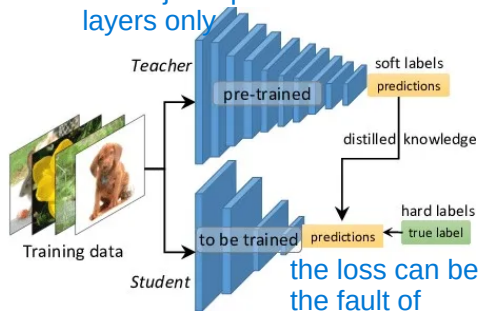
2. Exponential Moving Average (EMA) Teacher
   - Teacher's weights are updated as EMA of the student's weights (smoothed version), allowing the teacher to gradually capture improvements
3. Teacher Knowledge-Distillation
   - Large pre-trained teacher model generates "soft" labels (using temperature scaling), which the (smaller) student uses as targets, combined with the hard labels (two objectives)

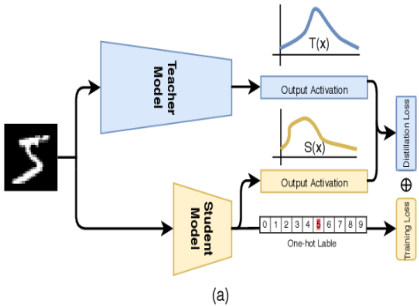
it is more over a fine tuning when we do exponential moving average.
as we just update the last layers only



the loss can be the fault of teacher as well as a student

Source: Image from https://towardsdatascience.com/knowledge-distillation-simplified-dd4973dbc764

4. Self-Distillation
   - Model serves as both teacher & student but at different stages of training (first supervised, later using own pseudo-labels) $\rightarrow$ layer distillation (knowledge from deeper layers to shallower), prediction distillation (re-use own predictions plus hard labels as targets)



Source: Image from Zeyi Tao et al., Neuron Manifold Distillation for Edge Deep Learning

Deep Learning Paradigms – Part I

Distillation Learning

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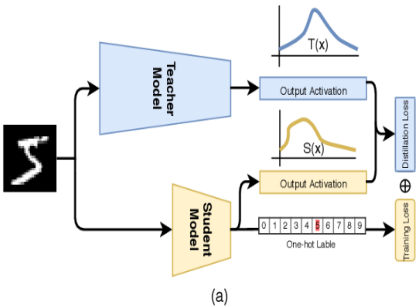
   - Model serves as both teacher & student but at different stages of training (first supervised, later using own pseudo-labels) → layer distillation (knowledge from deeper layers to shallower), prediction distillation (re-use own predictions plus hard labels as targets)
5. Noisy Student Training
   - Strong pretrained teacher model, while the student is trained with noisy inputs (strong augmentations, dropout, ...) learning semantic similarity



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Deep Learning Paradigms – Part I

Distillation Learning

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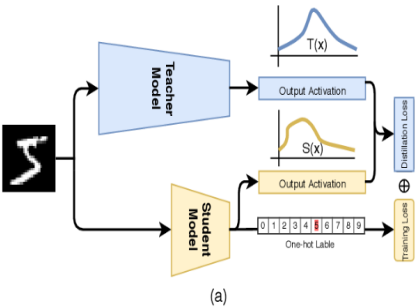
   - Strong pretrained teacher model, while the student is trained with noisy inputs (strong augmentations, dropout, ...) learning semantic similarity
6. Teacher-Student Co–Teaching
   - Models teach each other by exchanging predictions during training, while the models using the other's predictions as targets → Various perspectives!



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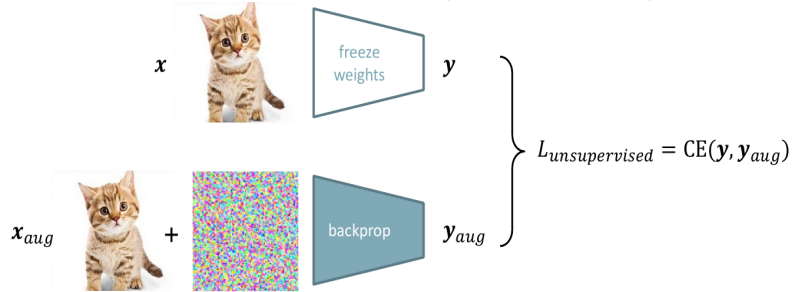
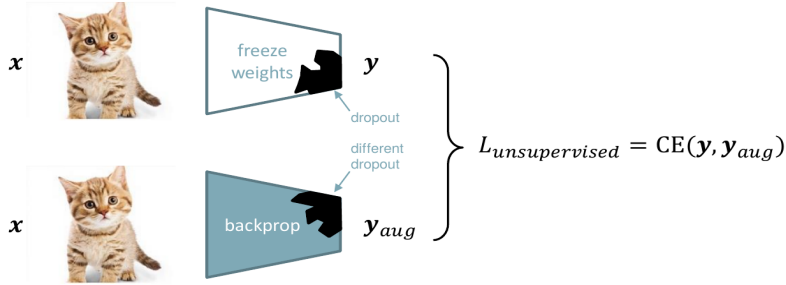
Consistency Regularization – Data Augmentation (Noise Distortion)



- Computing the unsupervised loss L_{unsup} by comparing the model prediction $y = f(x)$ with the model prediction using the augmented input $y_{aug} = f(x_{aug})$
- Similar samples x_{aug} are computed via Noise-Augmentation
- Similar/Close Inputs = Similar/Close Predictions

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Consistency Regularization – Network Modifications (Dropout)

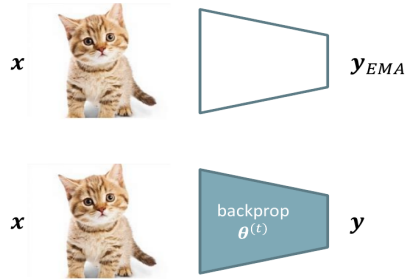


- Computing the unsupervised loss L_{unsup} by comparing the model prediction $y = f(x)$ with the model prediction using the augmented input $y_{aug} = f(x_{aug})$
- Identical training samples x for both models (changing data VS. changing models)
- Differing student-teacher models, e.g. by using distinct dropouts

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Consistency Regularization – EMA Student-Teacher Concept

$$\theta_{EMA}^{(t)} = \alpha\theta_{EMA}^{(t-1)} + (1-\alpha)\theta^{(t)}$$

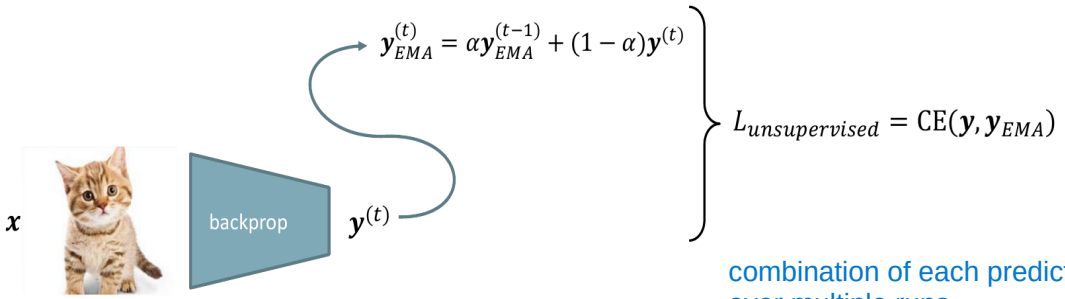


here we dont have freezed weightts but we move teacher with EMA wrt student weights.
here we provide stable target to student and then allows the student to learn,
basically we give time to student tp learn if we have hight erroe in past it is weighted less

- The teacher's weights are updated as an exponential moving average (EMA) of the student's weights, making the teacher a "smoothed" version of the student over time
- The EMA approach provides a stable target for the student, while allowing the teacher to gradually capture improvements as the student learns

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Consistency Regularization – Temporal Ensembling Student-Teacher Concept

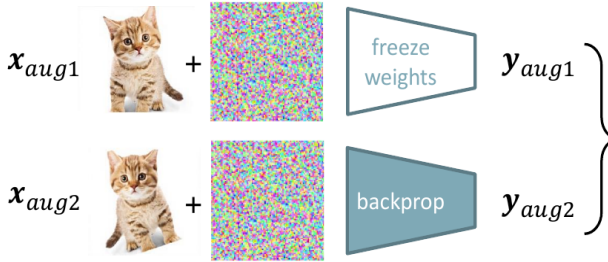


combination of each prediction over multiple runs

- Instead of maintaining a separate teacher, temporal ensembling aggregates the student's predictions over multiple training epochs, to build an ensemble prediction of each sample
- Ensemble prediction acts as a "teacher" for future student predictions, stabilizing learning without an explicit teacher model → Smoothed "ensemble" prediction!

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Consistency Regularization – Combining Approaches



$$L_{unsupervised} = \mathrm{CE}(y_{aug1}, y_{aug2})$$

the loss can be computed only by disctance mesurements

in these models we can only use distance measuments

- Computing the unsupervised loss L_{unsup} between two augmented, noise-distorted versions of a given (unlabeled) input $y_{aug_1} = f(x_{aug_1})$ and $y_{aug_2} = f(x_{aug_2})$
- Compare and see also Π-Model → 2× Augmentation + Noise + Dropout
- Other loss functions than CE-Loss possible (MSE-Loss/L2-Loss,...)

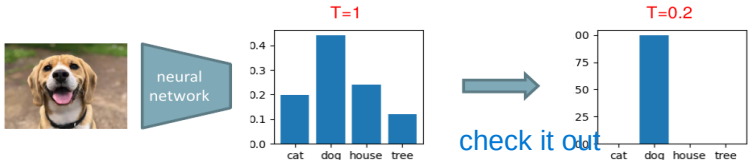
Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Deep Learning Paradigms – Part I

Semi-Supervised Representation Learning – Handling Unlabeled Data?

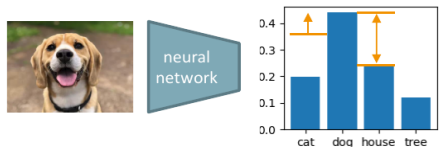
higher the entorpy the more uncertian the model is

Consistency Regularization – Softmax Temperature Scaling & Confidence Masking



check it out

- Softmax using temperature scaling parameter τ (learnable!) to sharpen predictions



i.e if model say 0.9 or more then i belive otherwize i wont

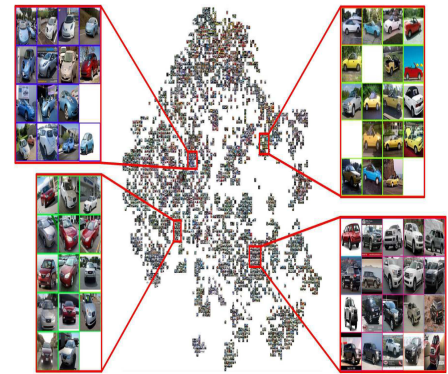
- Only consider samples for unsupervised loss where the classifier is confident (confidence-based masking) largest value $> x$, margin between largest/second largest value $> x$, entropy $\mathbb{H} = -\sum y_c log(y_c) < x$

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Deep Learning Paradigms – Part I

Deep Metric Learning

- Goal: Learn and structure the feature space where similar instances are closer together, and dissimilar instances are further apart

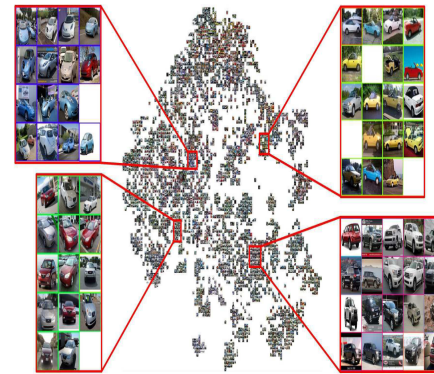


Source: Image from Yueqi Duan et al., Deep Adversarial Metric Learning

Deep Learning Paradigms – Part I

Deep Metric Learning

- Goal: Learn and structure the feature space where similar instances are closer together, and dissimilar instances are further apart
- Latent Embedding Space: mapping samples to a continuous vector space to use distance measurements between points reflecting their similarity



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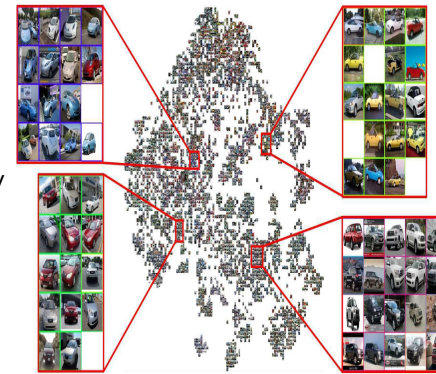
- Distance Metric: Euclidean distance and cosine similarity to quantify similarity between data samples



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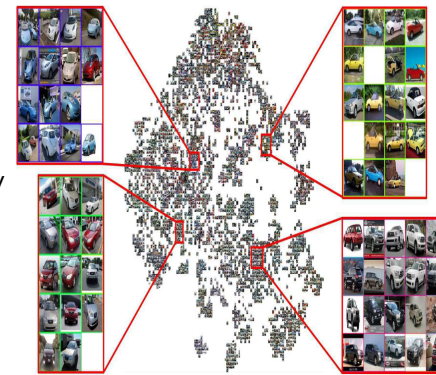
- Latent Embedding Space: mapping samples to a continuous vector space to use distance measurements between points reflecting their similarity
- Distance Metric: Euclidean distance and cosine similarity to quantify similarity between data samples
- Loss Functions:
  - Contrastive Loss: minimizes distance for similar pairs, maximizes distance for dissimilar pairs
  - Triplet Loss: ensures the anchor point is closer to a positive example than a negative example
  - N-pair Loss: generalizes triplet loss with multiple negatives

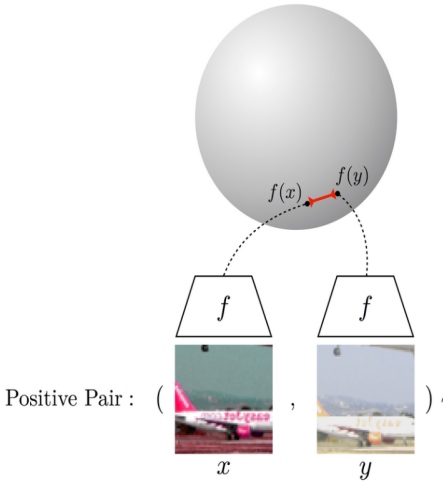


Source: Image from Yueqi Duan et al., Deep Adversarial Metric Learning

Deep Learning Paradigms – Part I

Contrastive Learning

- Goal: learning hidden (latent) representations by contrasting positive and negative pairs



Source: Image from Tongzhou Wang et al., Understanding Contrastive Representation Learning through Alignment and Uniformity on the Hypersphere

Deep Learning Paradigms – Part I

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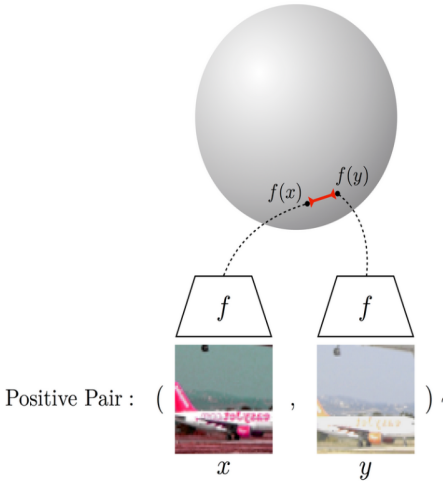
- Goal: learning hidden (latent) representations by contrasting positive and negative pairs
- Self-supervised Learning: No labels needed, uses data augmentations to create positive pairs (different views of the same instance)



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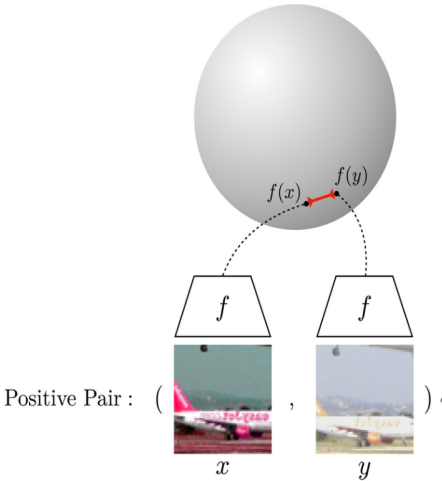
  - Negative pairs: Samples from different instances



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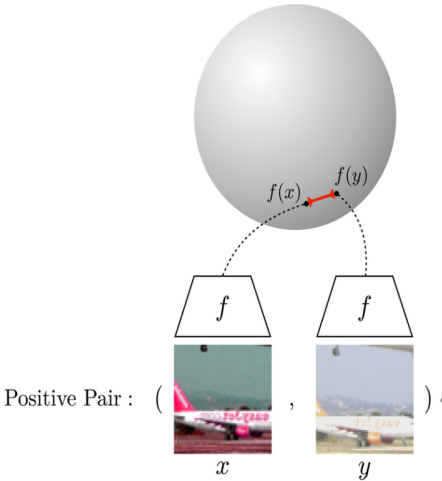

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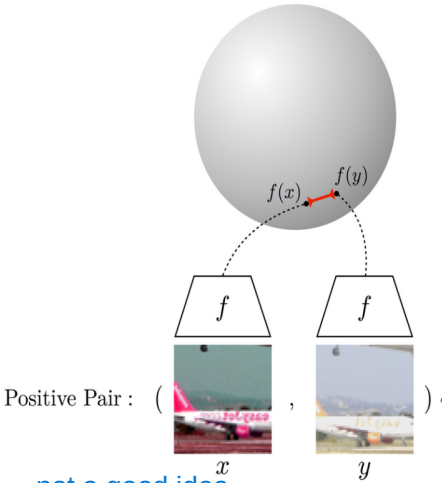
- Instance Differentiation: Each instance is considered its own class, creating highly discriminative representations



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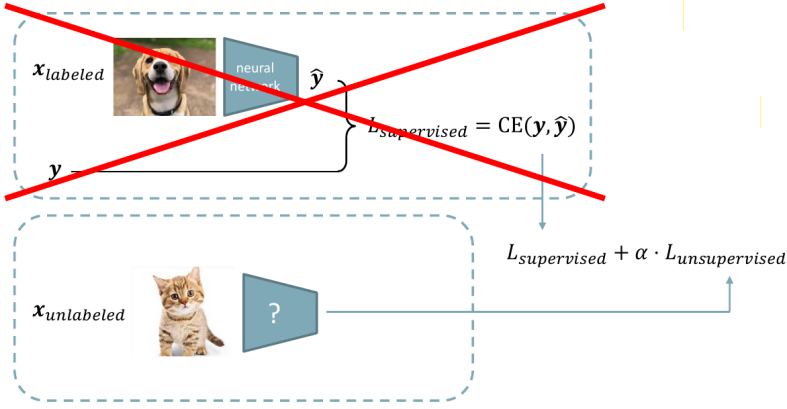
Deep Learning Paradigms – Part I

Contrastive Learning

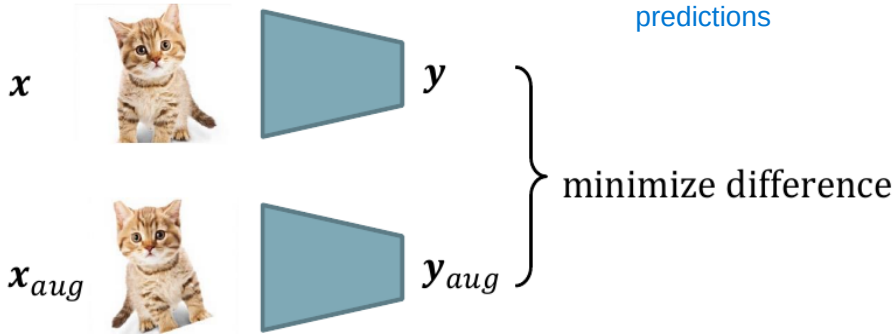


- Goal: (Semi-)Supervised learning always requires labeled data → How about computing similarities in a completely unsupervised fashion to build a classification model?

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

OTH Amberg-Weiden

our goal is to minimize the distance between two predictions



- In semi-supervised learning, a set of augmented data samples x_{aug_n} was created in order to build similar input pairs x/x_{aug_n} (no labeling required!), which should result in similar predictions y/y_{aug_n} according to the smoothness assumption → Minimizing Difference!

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

similar to BCE intresting!!!! check it out

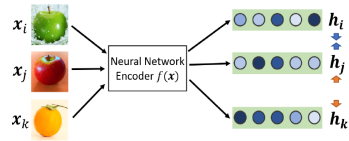
squared l2 norm

here it is epsilon - squared l2 norm nout belong to

Contrastive Loss

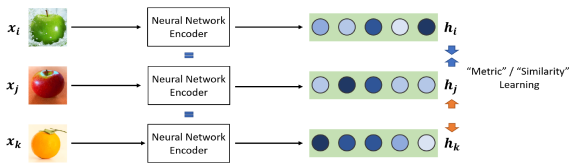
- Contrastive loss works with pairs, while each can either be a positive pair (two similar examples) or a negative pair (two dissimilar examples)
- $L(x_i, x_j) = y \cdot ||f(x_i) - f(x_j)||_2^2 + (1-y) \cdot max(0, \epsilon - ||f(x_i) - f(x_j)||_2^2)$ with $y = 1$ (positive pair) and $y = 0$ (negative pair)
- Minimize distance between embeddings of positive pairs and maximize the distance for negative pairs, up to a certain margin ϵ

epsilon is the raidus here



xk

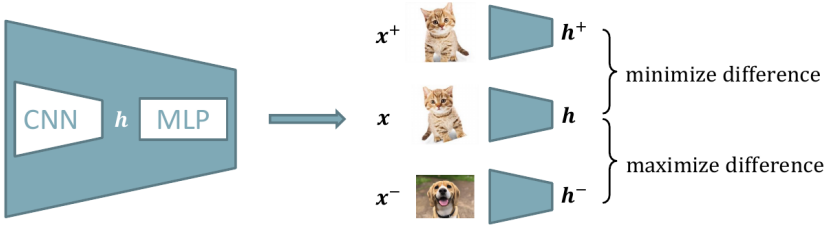
check it out



when distance is hure epsilon-l2 norm will take zero which means our negative pair is far away and our loss is zero

Source: Image from FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Representation Learning

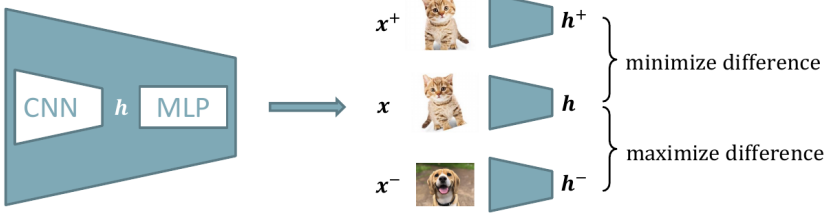
Triplet Loss



- Extend the pair consisting of an unlabeled data sample x and a (similar) augmented version $x_{aug_n} = x^+$ to a triplet by introducing a dissimilar sample x^-

Source: Image from OTH-AW. Electrical Engineering, Media and Computer Science. Thomas Nierhoff – Vorlesung Advanced Topics in ML

Triplet Loss



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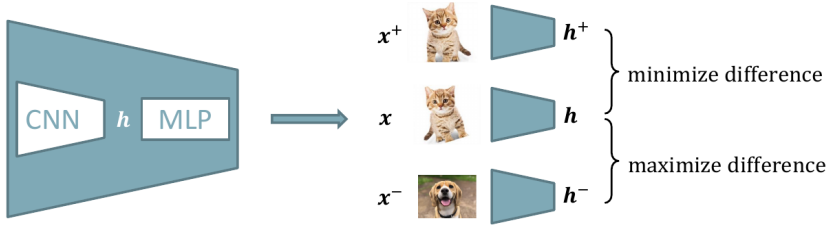

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Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

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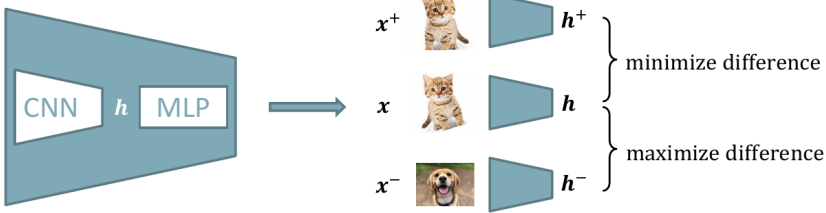

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- Contrastive learning is about to organize the latent feature space!

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

- Contrastive Loss: general idea of forcing to move the original sample h (anchor, blue) towards the positive sample h^+ (positive, green) and away from the negative feature h^-(negative, red)

$$L = ||h - h^+||_2^2 + max(0, \epsilon - ||h - h^-||_2^2) = max(0, ||h - h^+||_2^2 - ||h - h^-||_2^2 + \epsilon)$$

known as Triplet-Loss, with: minimization $||h - h^+||_2^2$, maximization $||h - h^-||_2^2$ up to ϵ

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Deep Learning Paradigms – Part I

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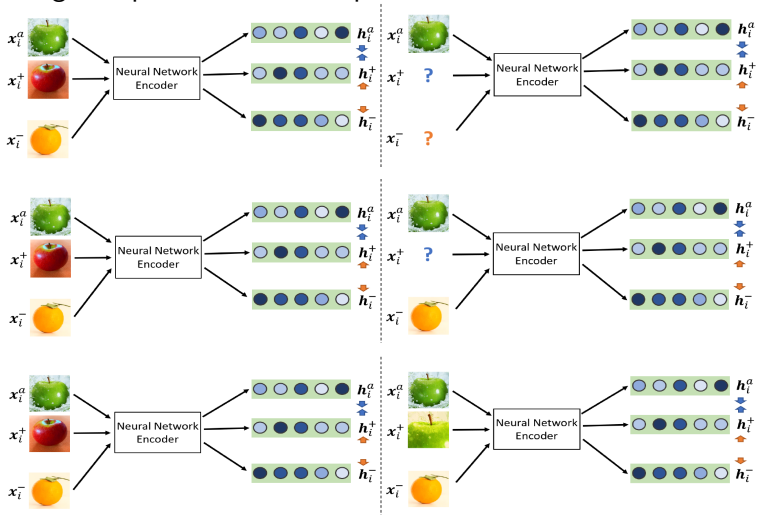
- Easy Triplets: $\delta(a, p) + \epsilon < \delta(a, n)$
- Semi-Hard Triplet: $\delta(a, p) < \delta(a, n) < \delta(a, p) + \epsilon$
- Hard Triplets: $\delta(a, n) < \delta(a, p)$

Source: Image from OTH-AW, Electrical Engineering, Media and Computer Science, Thomas Nierhoff – Vorlesung Advanced Topics in ML

Deep Learning Paradigms – Part I

Contrastive Learning – Supervised VS. Unsupervised



Source: Images from FAU Erlangen-Nuremberg, Pattern Recognition Lab, K.Breininger, V. Christlein, Advanced Deep Learning – Representation Learning

Further Questions?

https://www.oth-aw.de/hochschule/ueber-uns/personen/bergler-christian/

Source: https://emekaboris.medium.com/the-intuition-behind-100-days-of-data-science-code-c98402cdc92c