INSTITUT FÜR
KUNSTSTOFFVERARBEITUNG
IN INDUSTRIE UND HANDWERK AN DER RWTH AACHEN

Analysis of transfer learning to transfer process knowledge when processing different materials

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Outline

- Motivation of applying transfer learning
- Dataset description and feature ranking
- Construction of DNN-ETL model
- Transfer performance analysis
- Application scenario of DNN-ETL
- Conclusion and outlook

[URL00]

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Motivation of applying transfer learning in injection molding

Conventional deep learning approach

Objective

To analyse the possibility to transfer knowledge between processes where different materials are being utilized.

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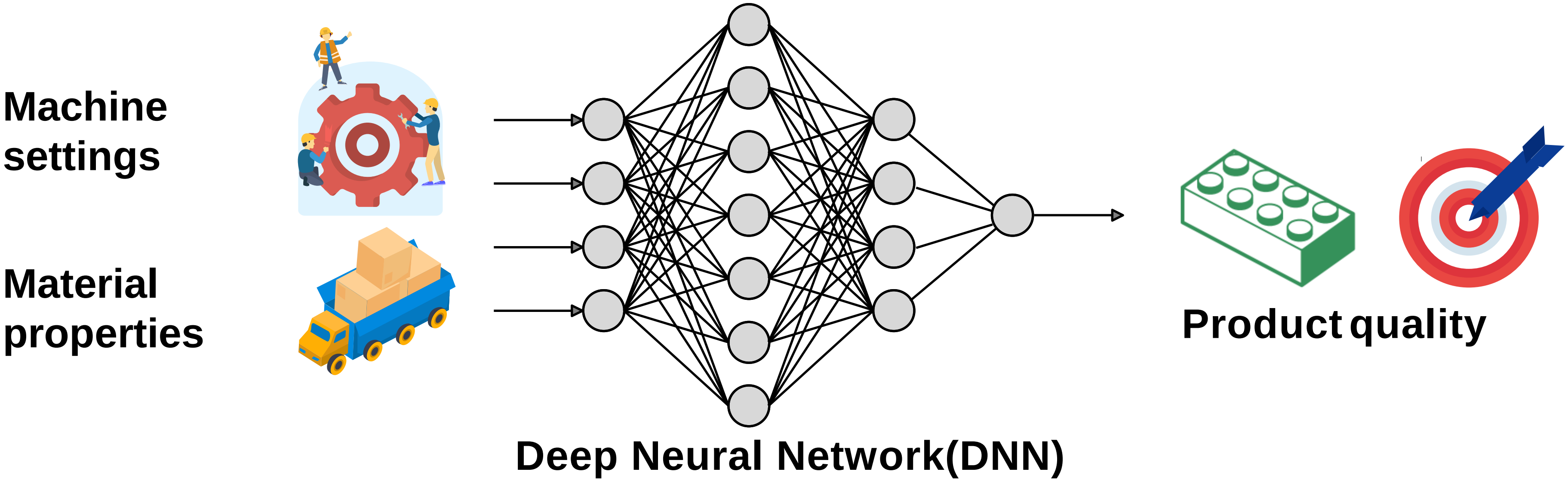

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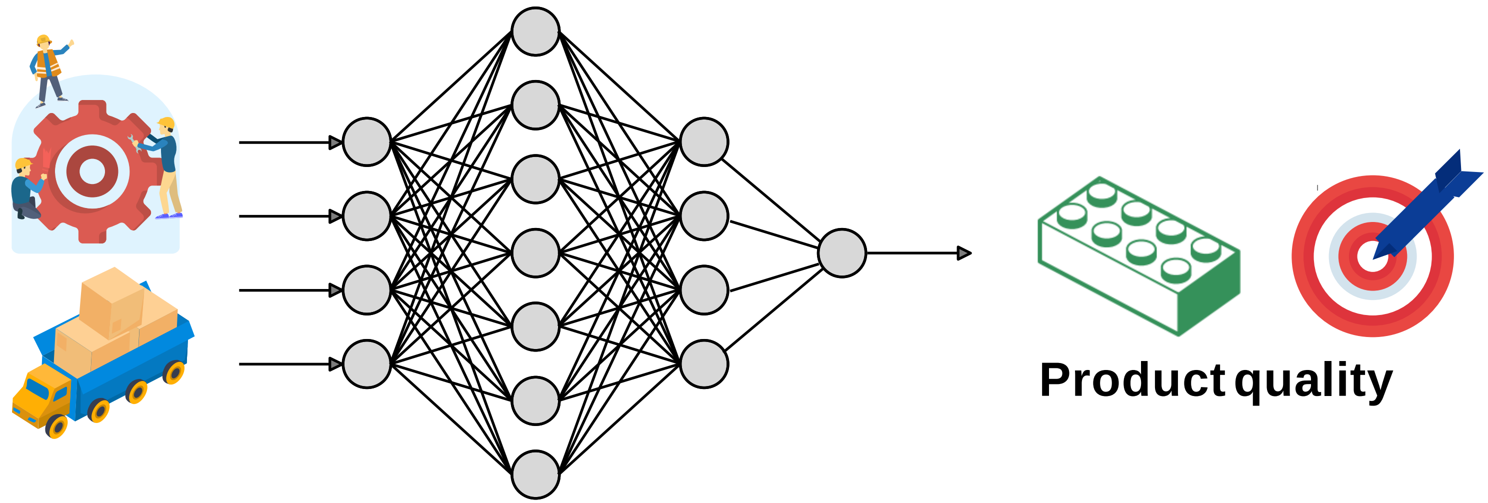


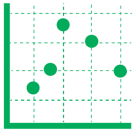
Challenges

- Require large amount of process data
- High training effort of the fitting models in the changes of production process

Conducting experiments with a new material

Source dataset

Large process databank of multiple materials



Target dataset

Several data points of a new material

Conducting experiments with a new material

Source dataset — Large process databank of multiple materials

- Related but different
- Same feature space
- Different distribution

Target dataset — Several data points of a new material

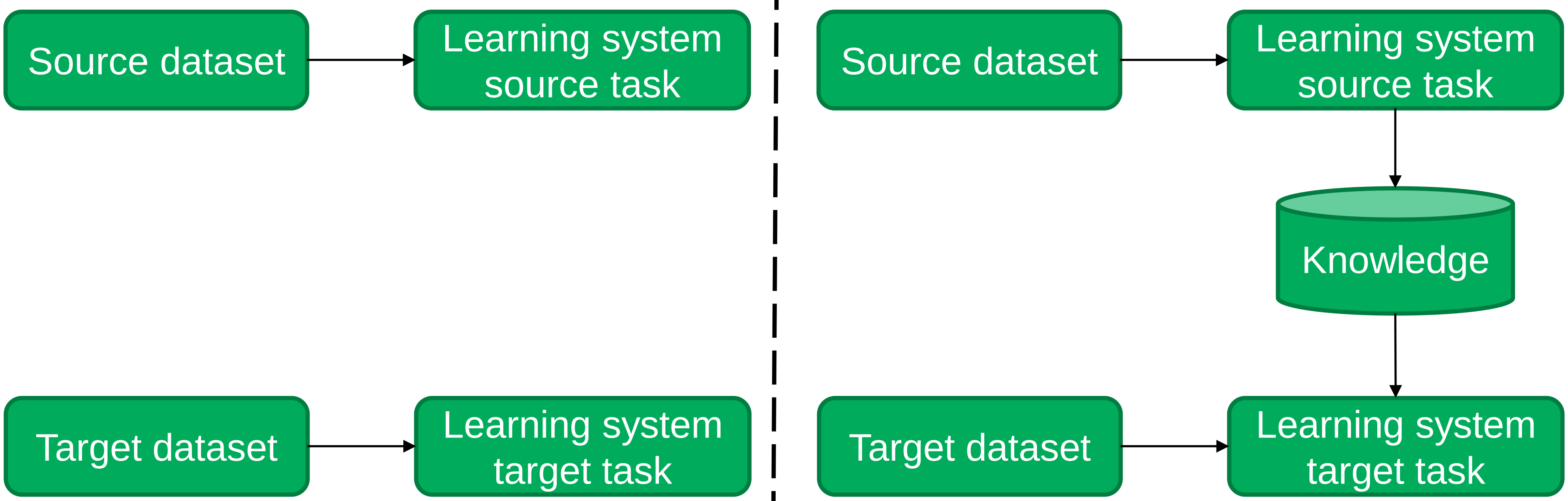
Comparison of conventional DNN and DNN with transfer learning

Conventional DNN

- Training is isolated
- Knowledge is not retained or accumulated

DNN-TL

- Training of a new task relies on the previous learned task
- Faster training, accurate, less training data



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Material series, polymer classes, manufacturers and amount

01 **APEC**

Polycarbonate
Company: Covestro
Amount: 13

02 **PLEXIGLAS**

Polymethylmethacrylat
Company: Evonik
Amount: 10

03 **ULTRAMID**

Polyamid
Company: BASF
Amount: 9

04 **VALOX**

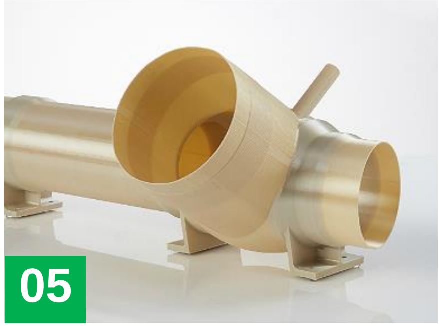
Polybutylenterephthalat
Company: Sabic
Amount: 4

05 **ULTEM**

Polyetherimid
Company: Sabic
Amount: 6

06 **SABIC PP**

Polypropylene
Company: Sabic
Amount: 17



[URL01]

Input and output variables of DNN model based on injection moulding simulation

CADMOULD® 3D-F SIMULATION

60 materials, 77 experiments for each one

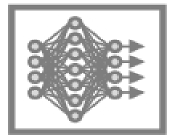
6 machine settings:

- Holding pressure. [bar]
- Holding pressure time [s]
- Melt temperature [℃]
- Cavity wall temperature [℃]
- Cooling time [s]
- Injection flow rate [cm³/s]

220 material properties:

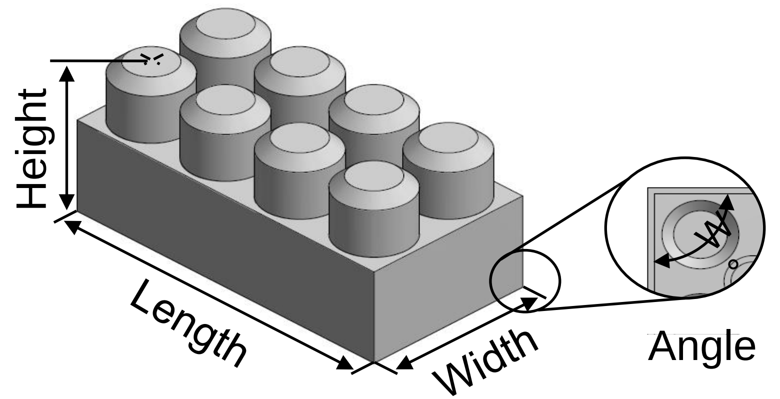
- Solid density [kg/m³]
- Melt density [kg/m³]
- Thermal conductivity $[W/m \cdot ℃]$

……



5 quality values:

- Part weight [g]
- Length [mm]
- Height [mm]
- Width [mm]
- Angle [°]



Toy building block with 4×2 studs

[Hei17]

Input and output variables of DNN model based on injection moulding simulation

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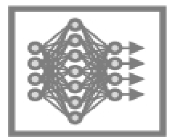
- Some features are not related



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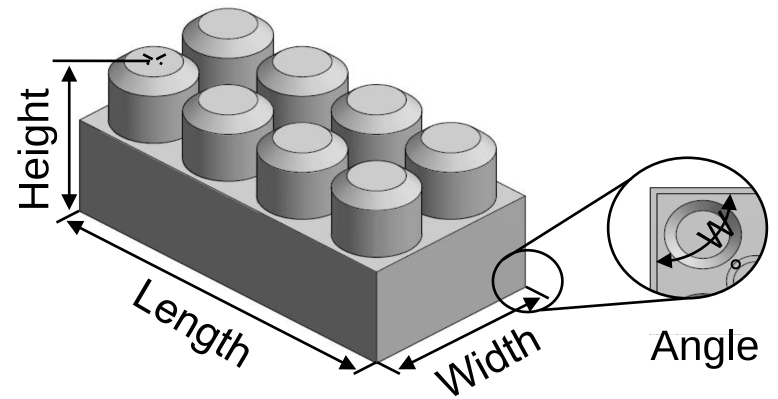

Toy building block with 4×2 studs

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Input and output variables of DNN model based on injection moulding simulation

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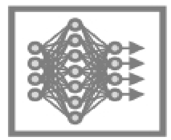

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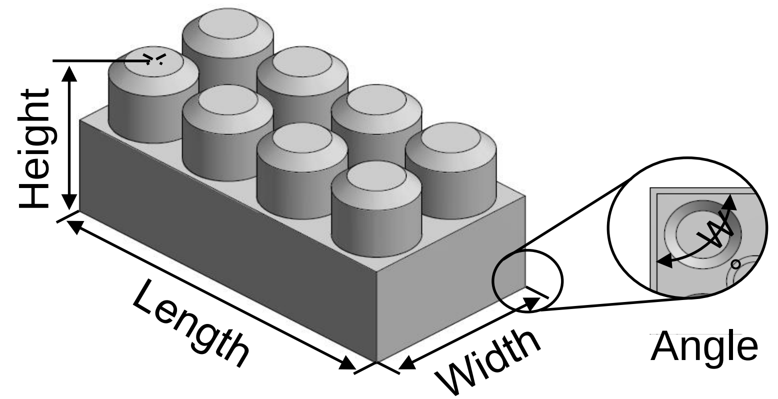


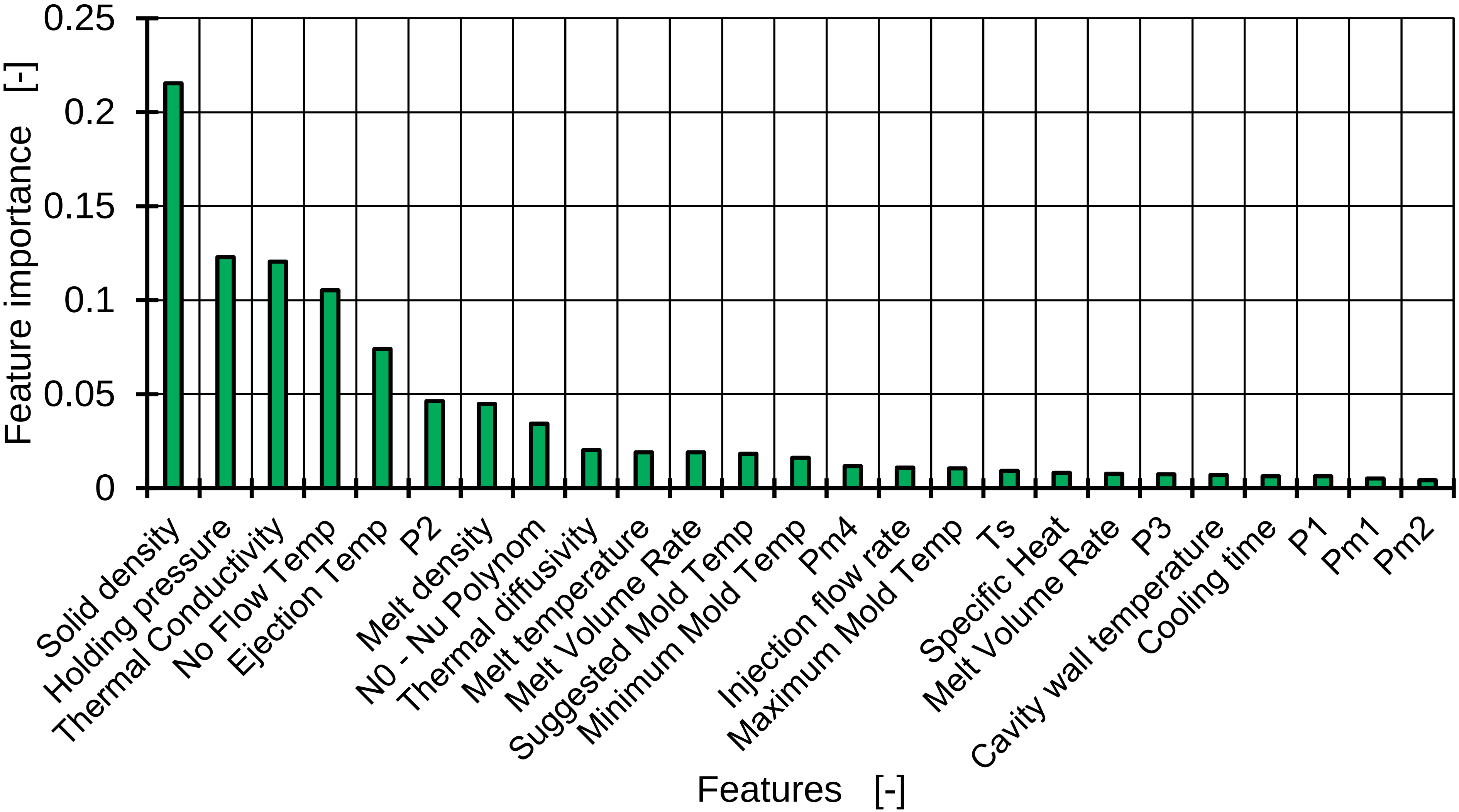
Toy building block with 4×2 studs

- Some features are not related

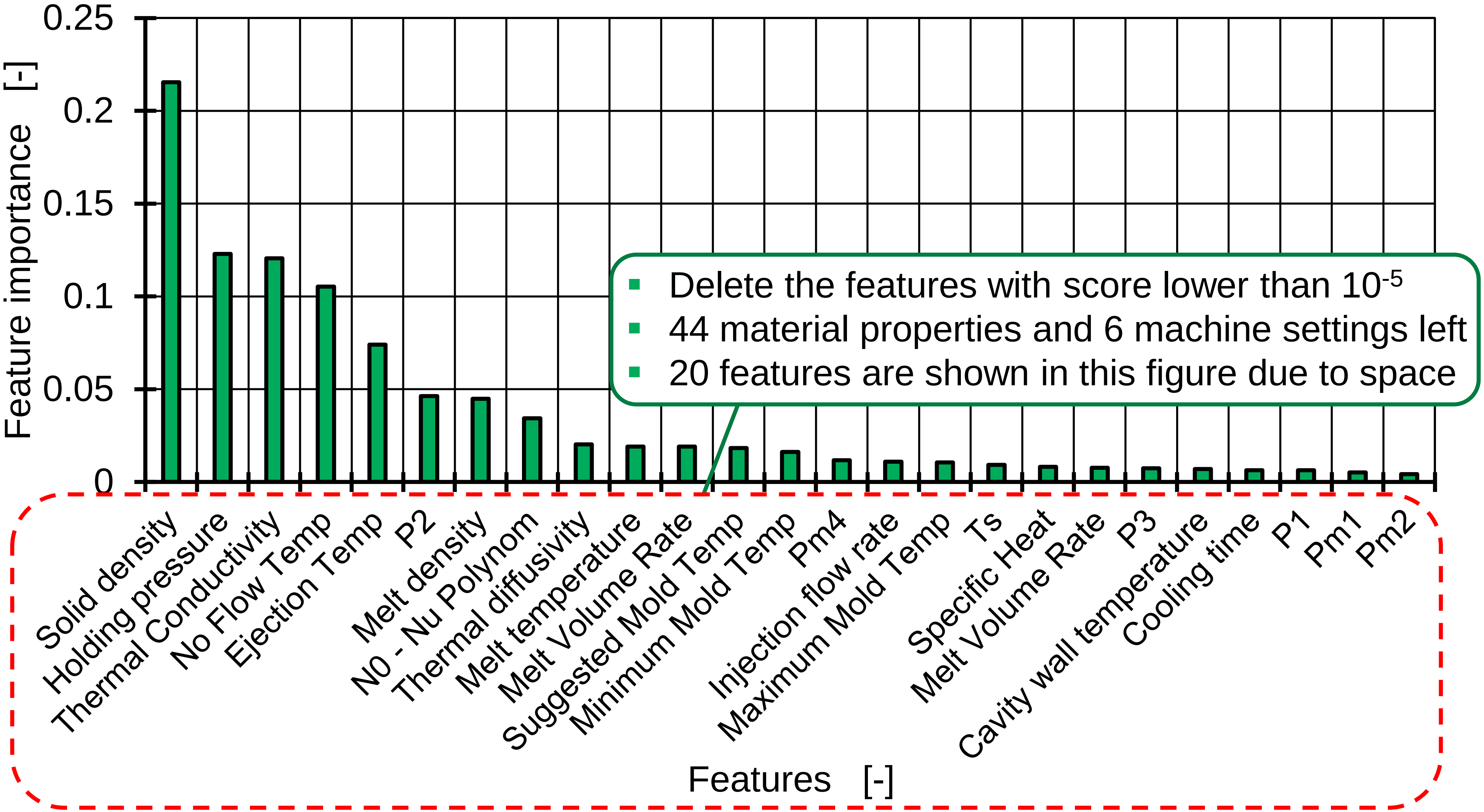
- Apply feature ranking method

[Hei17]

Feature importance score ranking for prediction of part weight

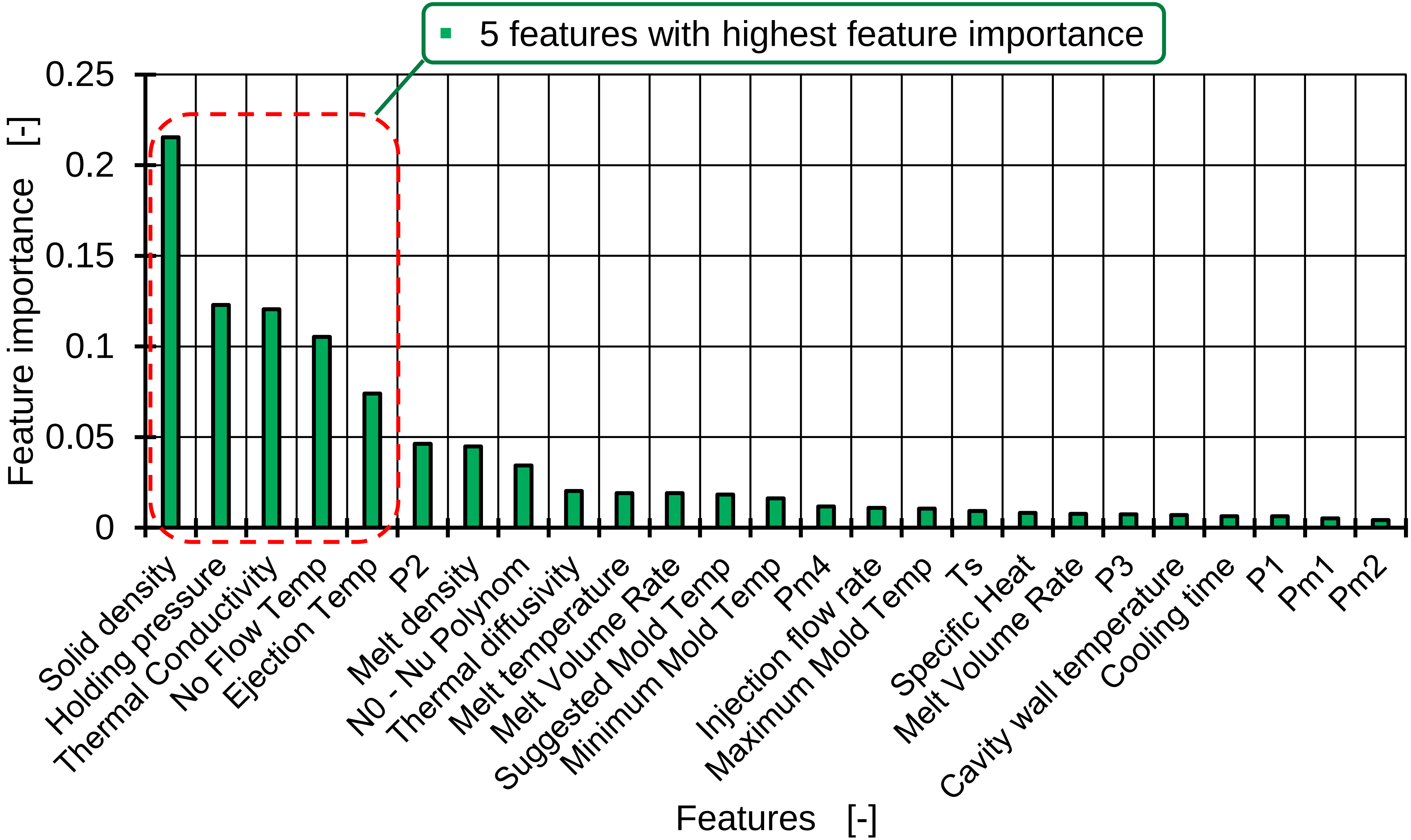


Feature importance score ranking for prediction of part weight

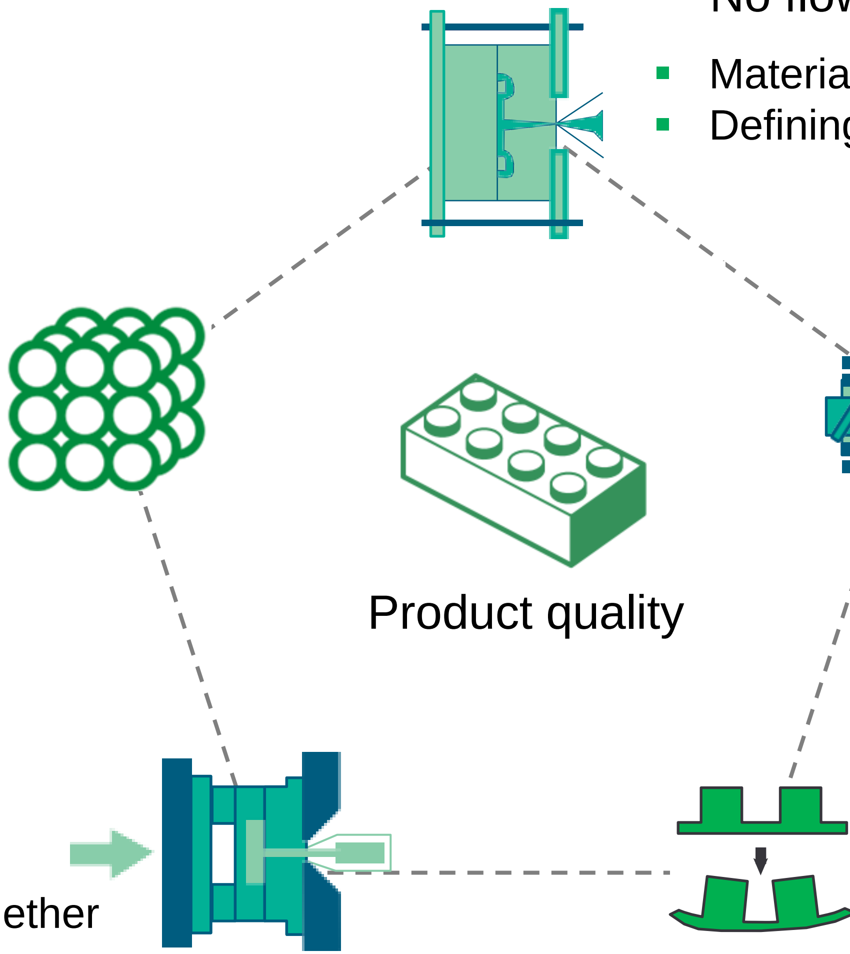


- Delete the features with score lower than 10^{-5}
- 44 material properties and 6 machine settings left
- 20 features are shown in this figure due to space

Feature importance score ranking for prediction of part weight



Analysis of 5 important influence factors



No flow temperature

- Material stops flowing below certain temp.
- Defining the amount of entering material

Solid density

- Related to part weight

Ejection temperature

- Influence shrinkage

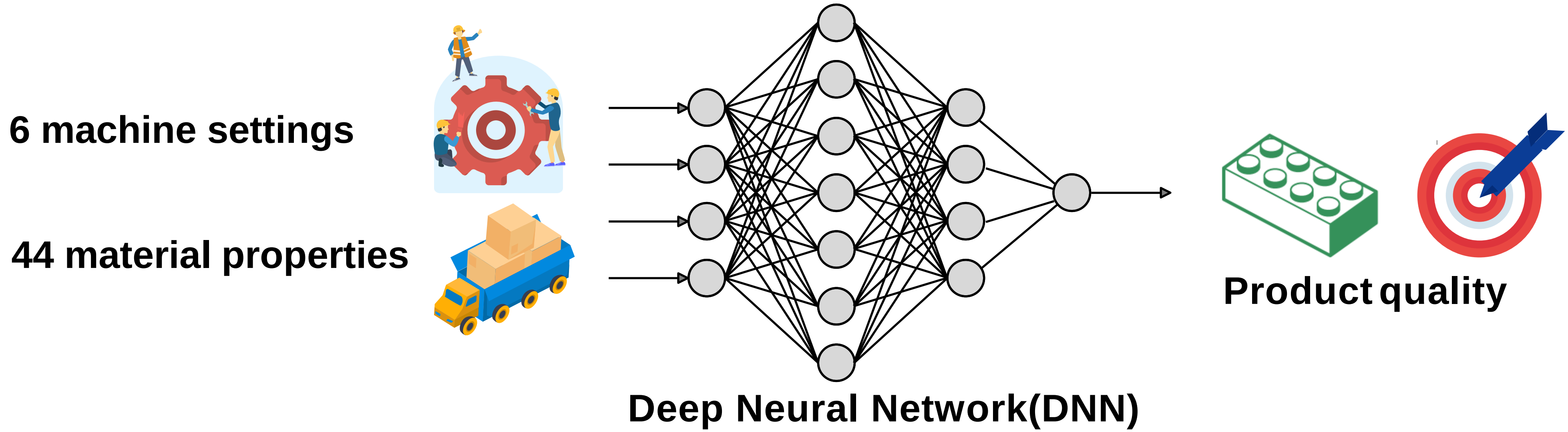
Holding pressure

- Packing molecules together in an orderly fashion
- Shrinkage compensation

Thermal conductivity

- Temperature distribution
- Warpage of the mould

Summary of the dataset



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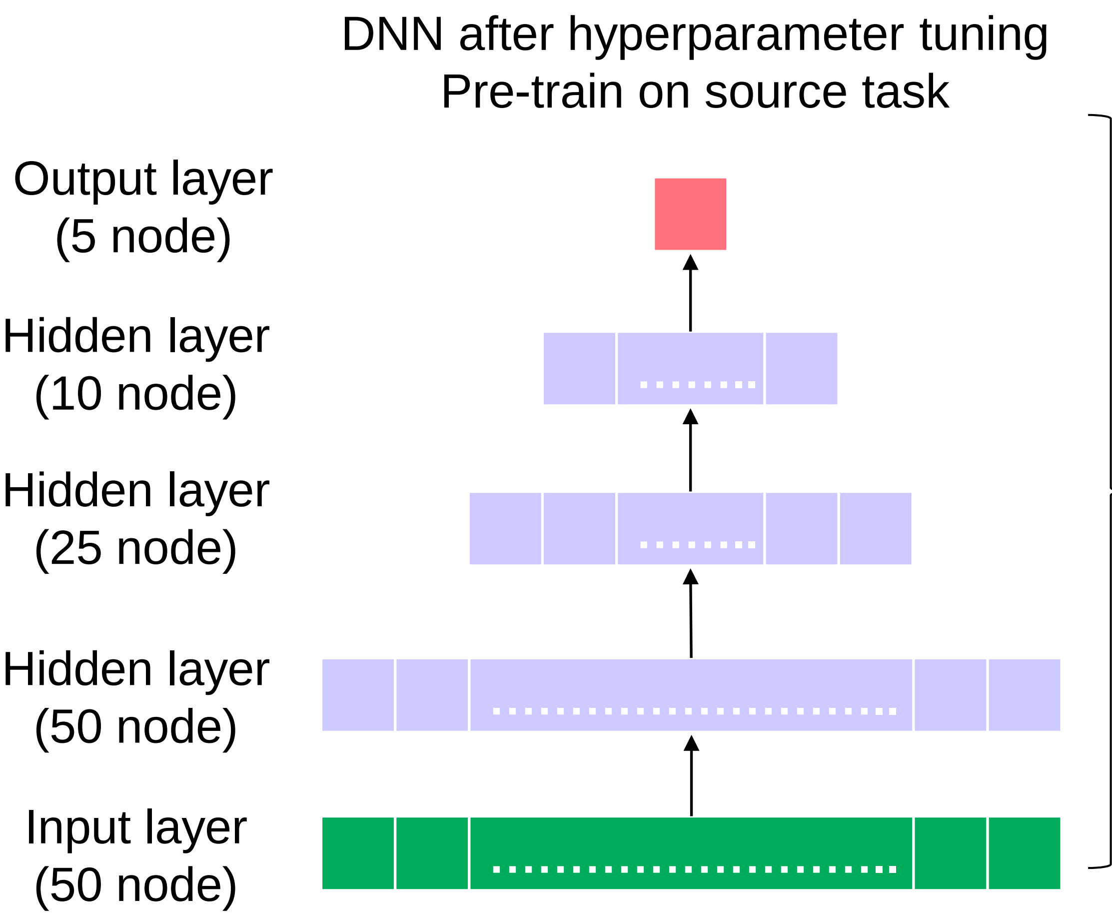
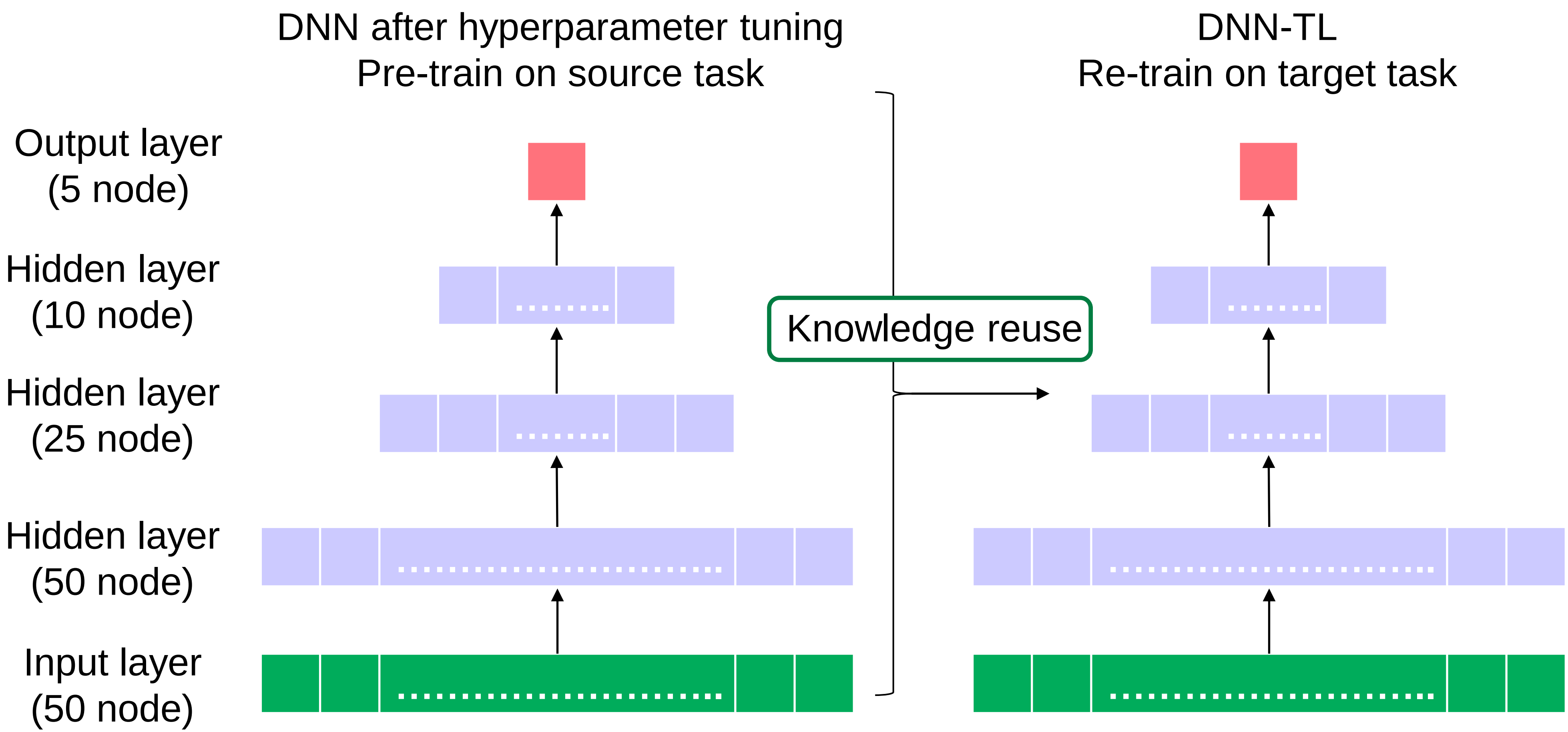
Structure of deep neural network (DNN)



Knowledge:
- DNN structure
- Weights
- Hyperparameters

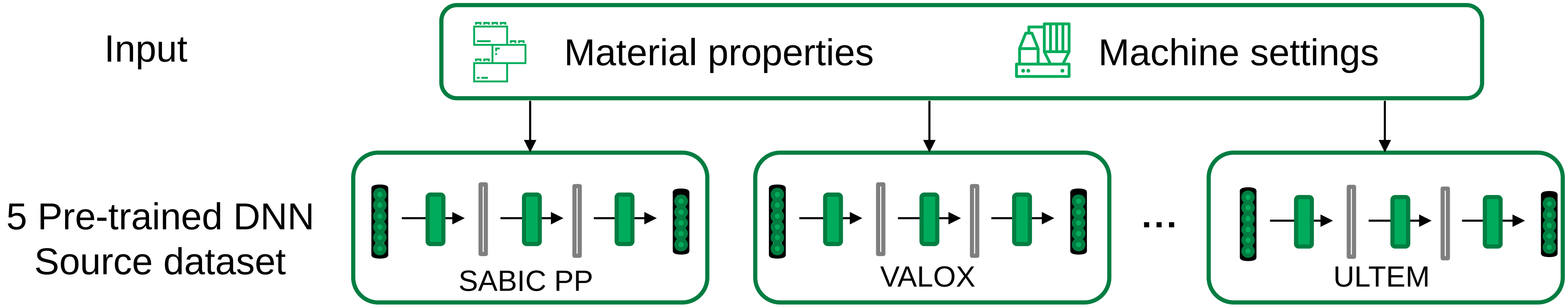
…

Structure of DNN with transfer learning (DNN-TL)

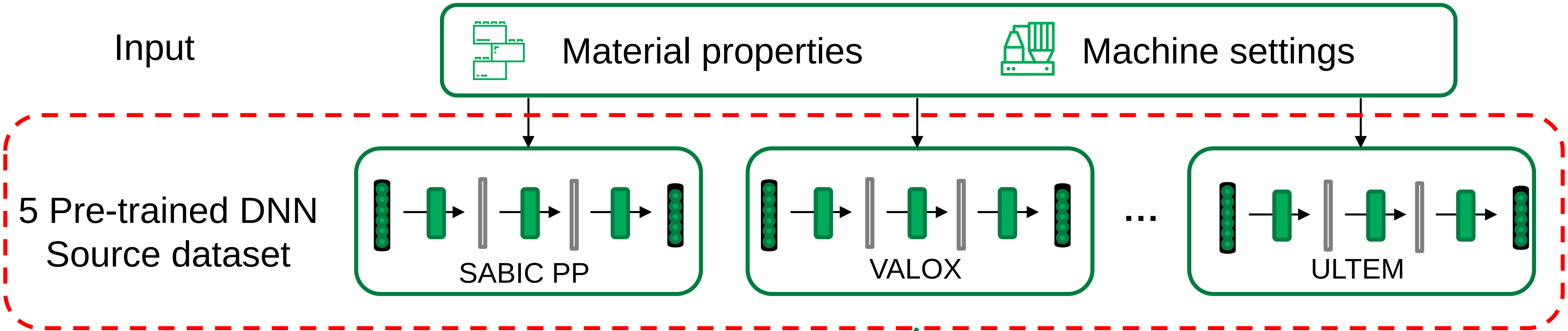


- Transfer knowledge **from one model to another model**

Structure of DNN with transfer and ensemble learning (DNN-ETL)

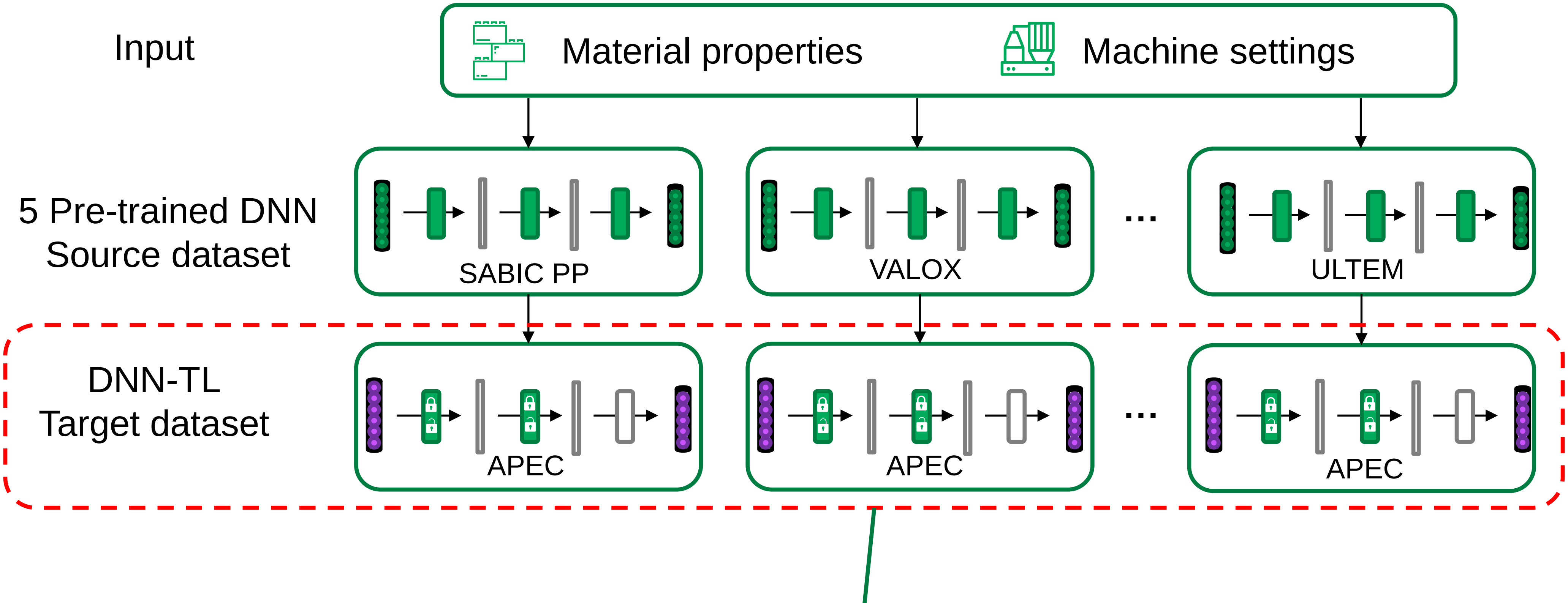


Structure of DNN with transfer and ensemble learning (DNN-ETL)



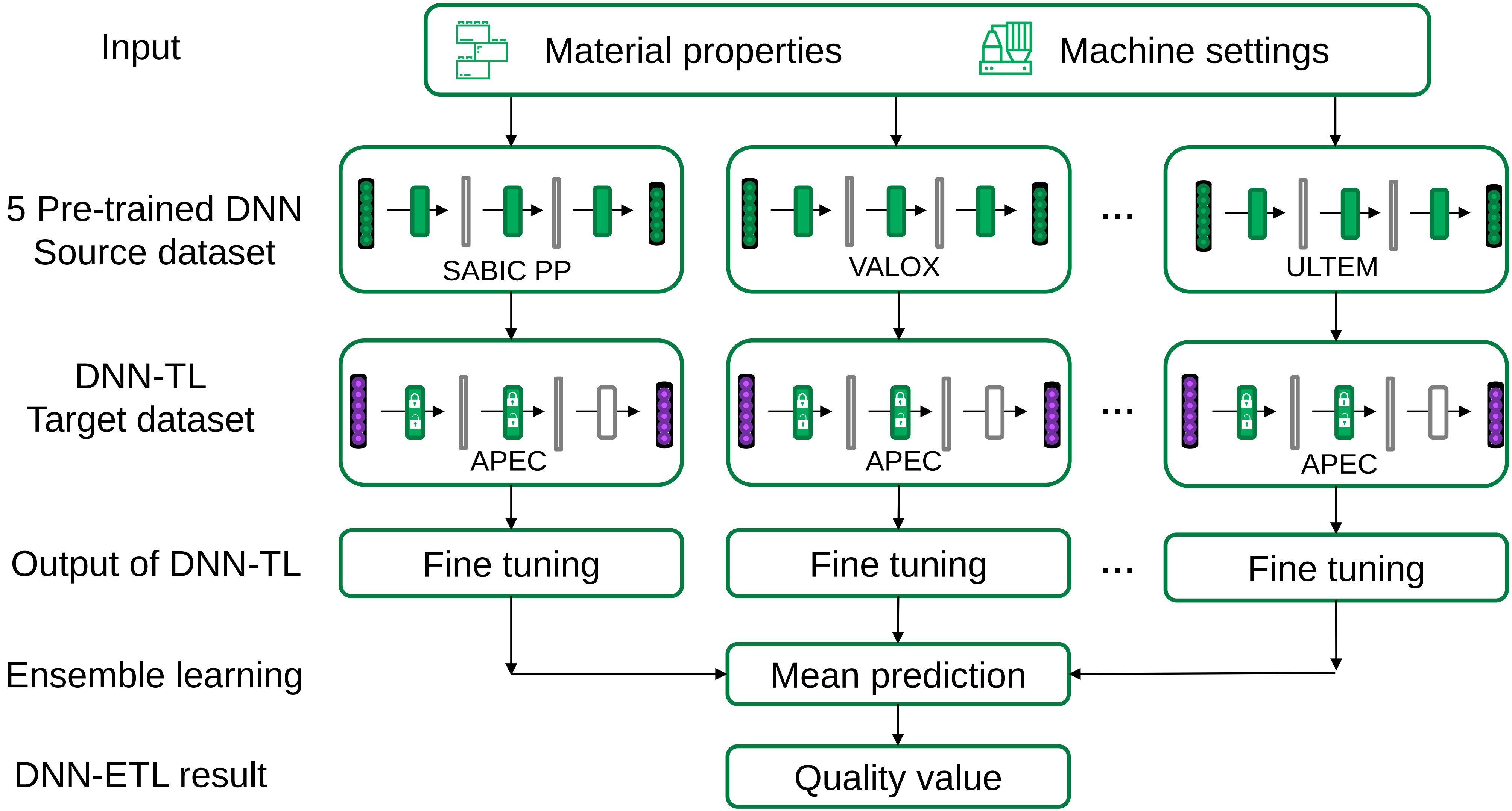
- 5 material classes are selected as source dataset
- Pre-train a DNN model on each of the material class

Structure of DNN with transfer and ensemble learning (DNN-ETL)



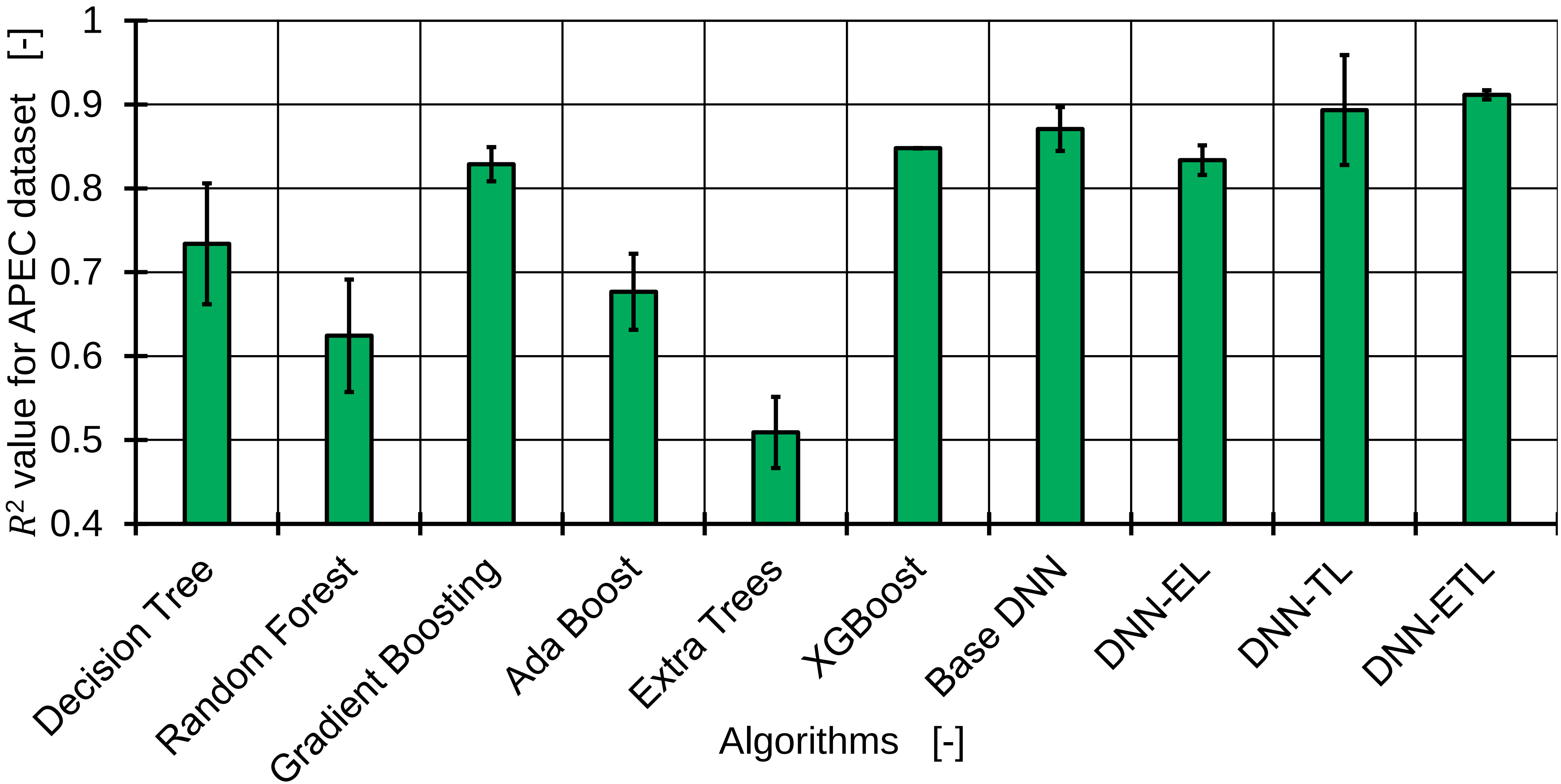
- APEC dataset are selected as target dataset
- Transfer knowledge **from five models to one model**

Structure of DNN with transfer and ensemble learning (DNN-ETL)



Model comparison of R^2 value

- Base DNN: without transfer and ensemble
- DNN-EL: with ensemble learning
- DNN-TL: with transfer learning
- DNN-ETL: with both transfer and ensemble



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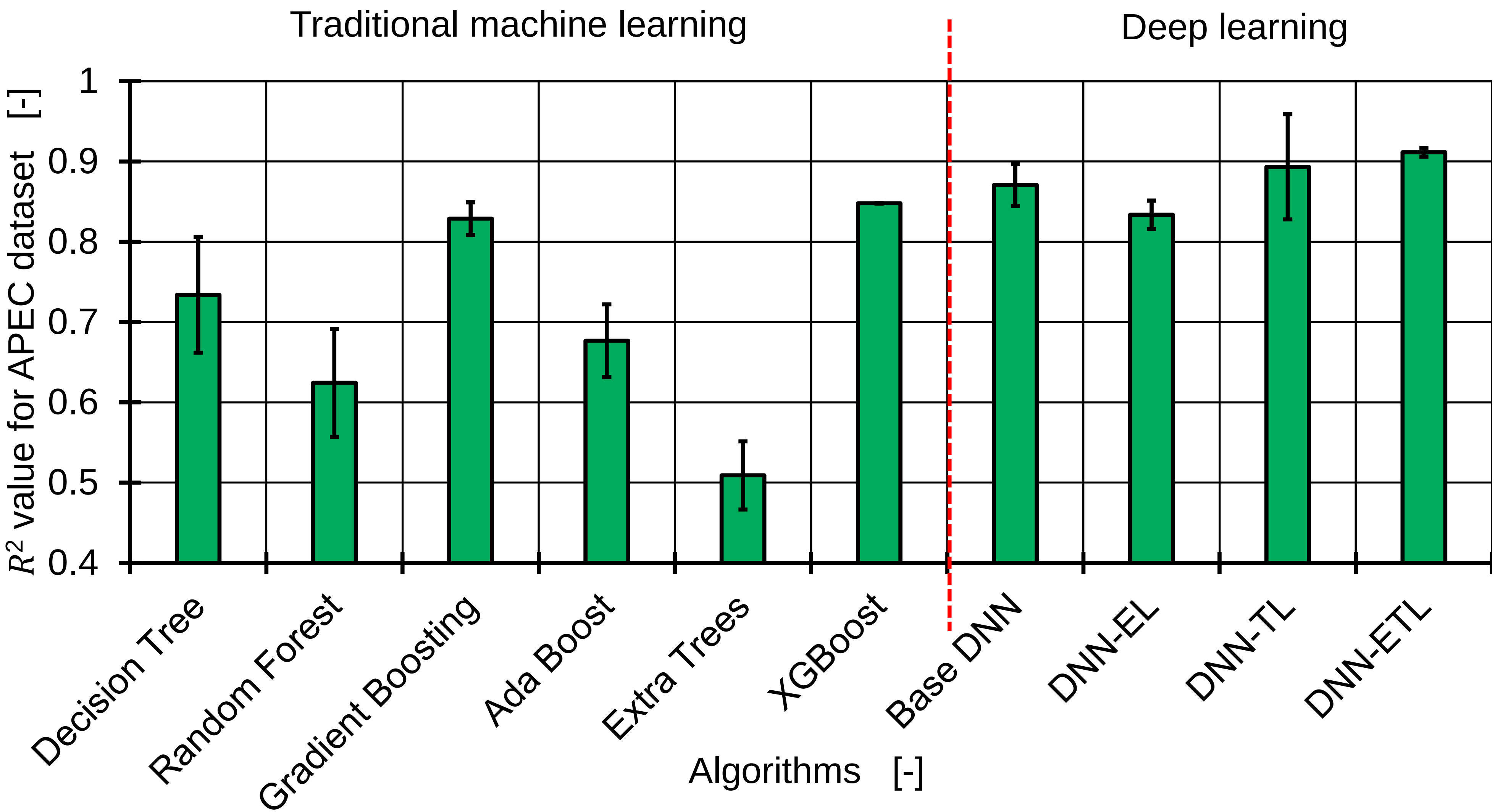

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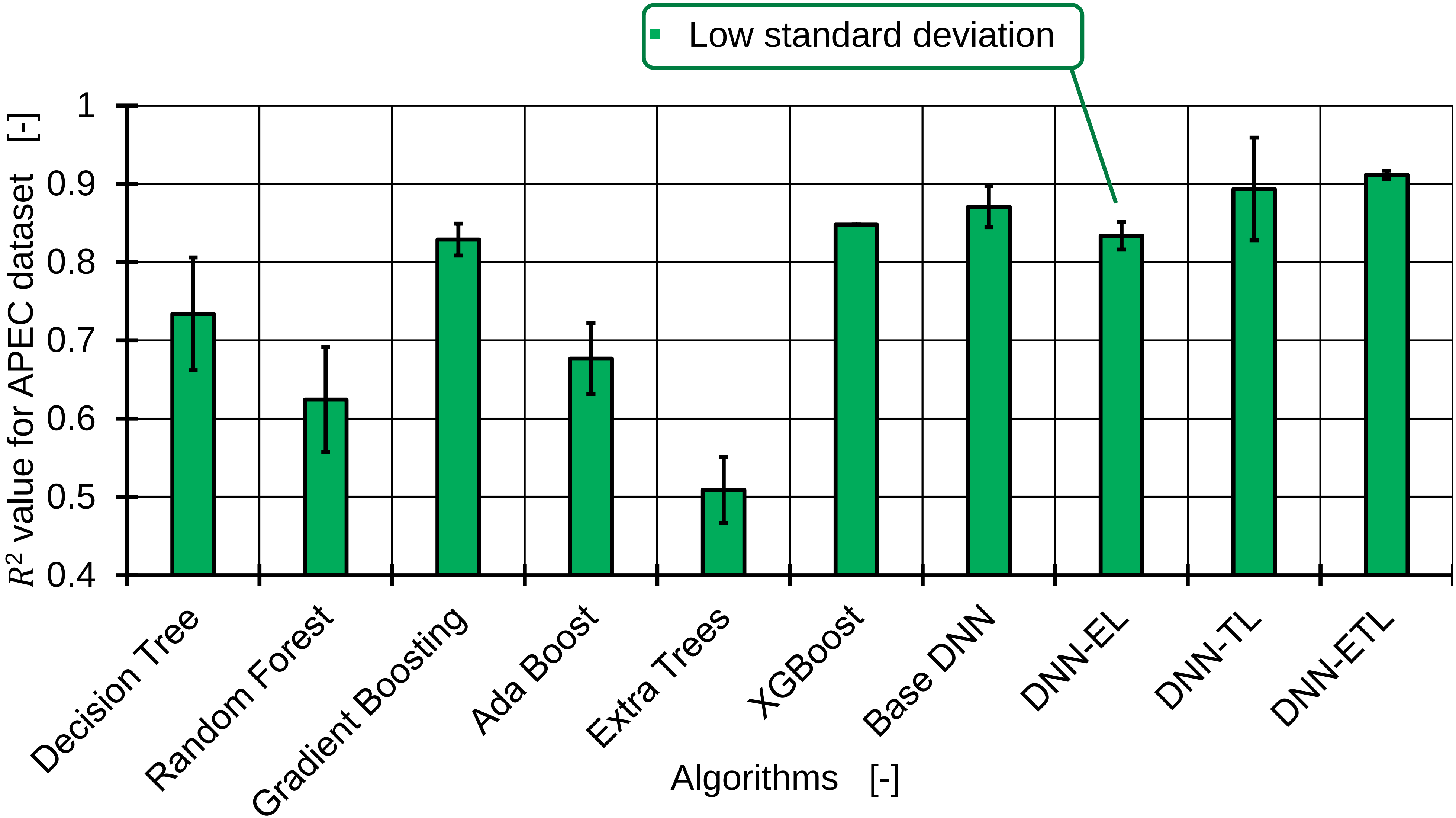
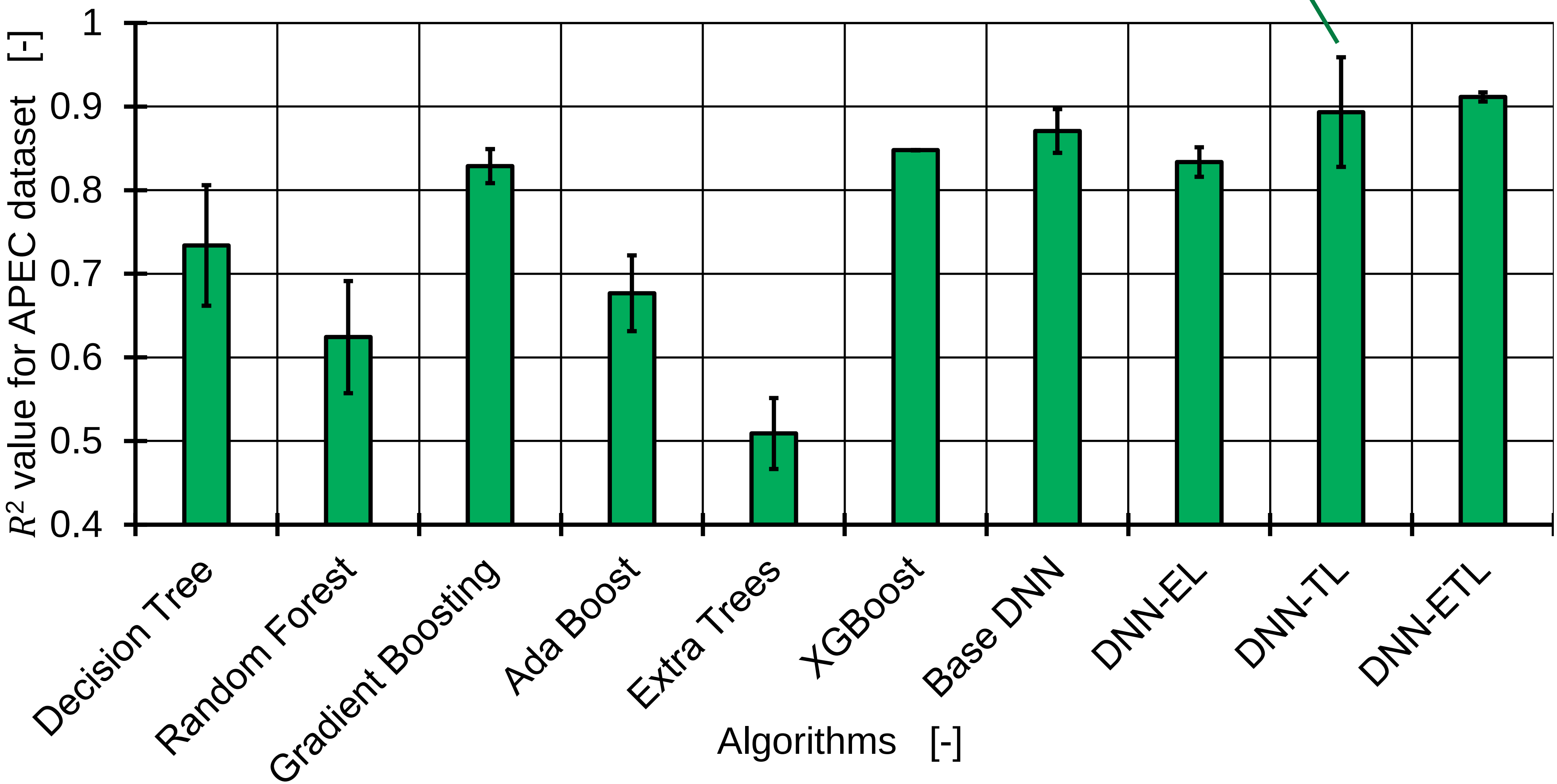


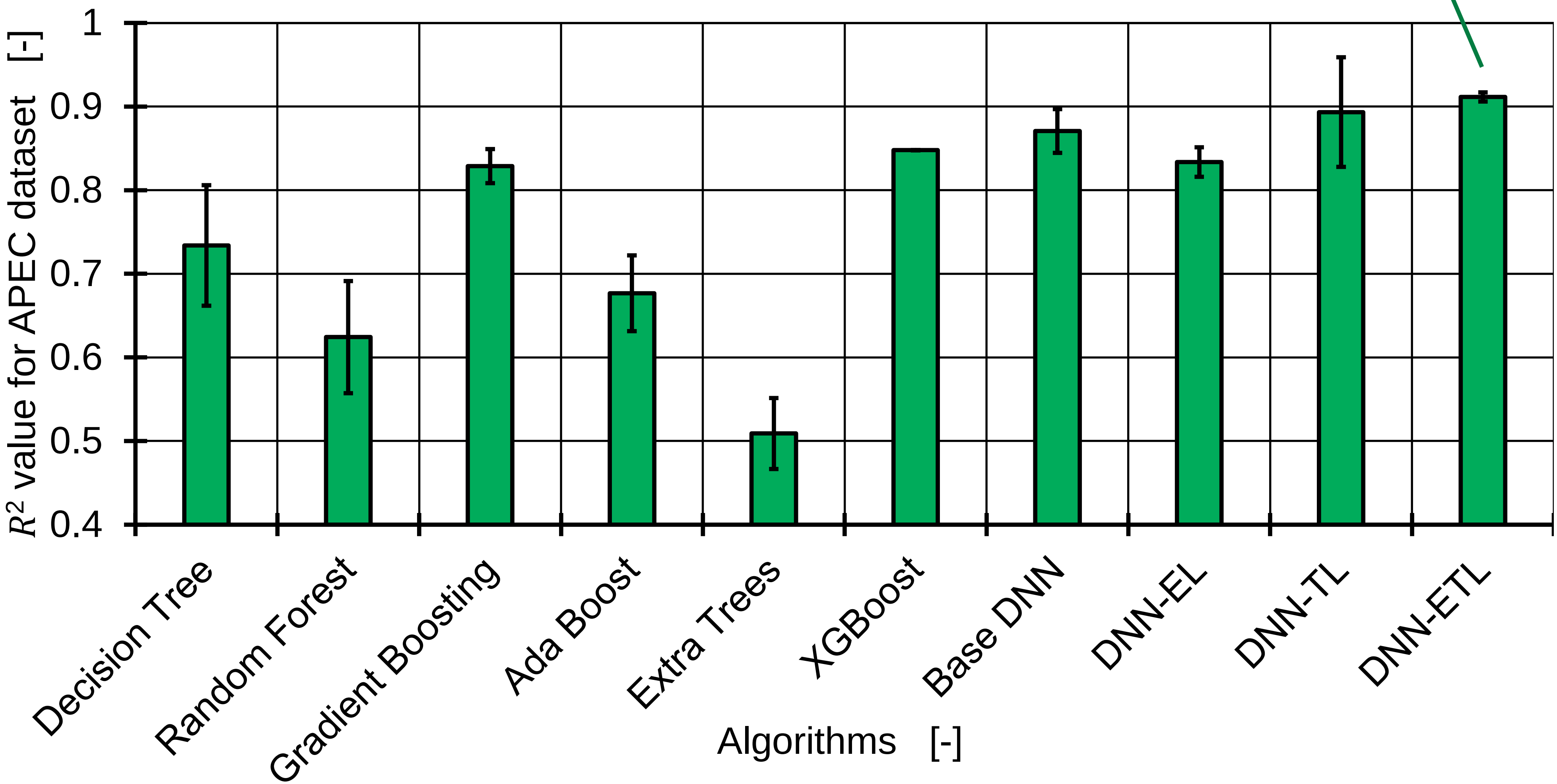
Model comparison of R^2 value

- Better performance
- High standard deviation



Model comparison of R^2 value

- Best performance 0.9207
- Low standard deviation



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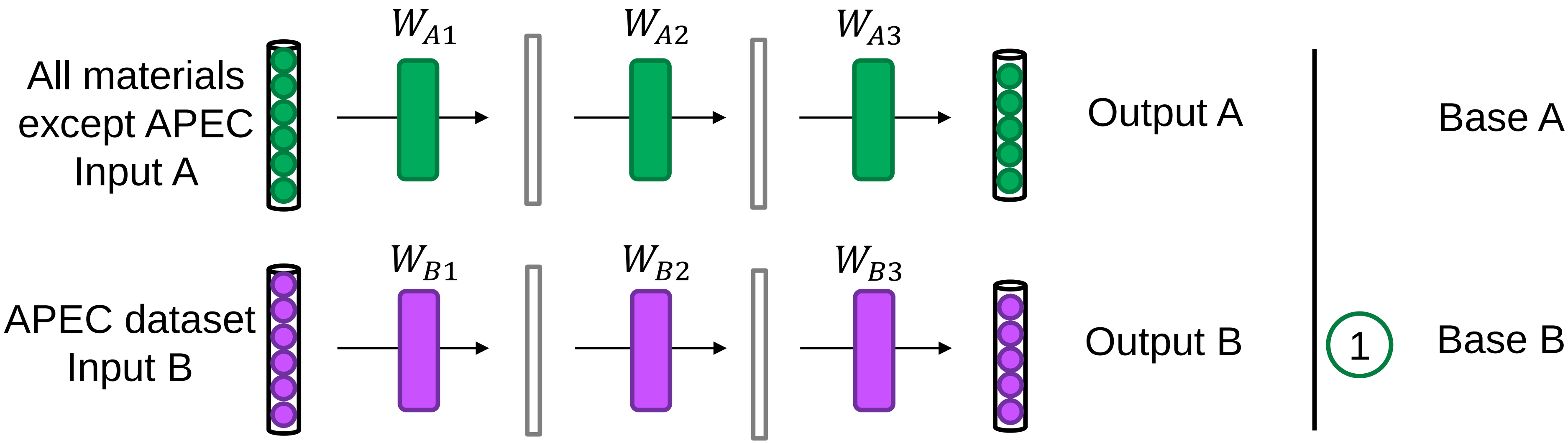
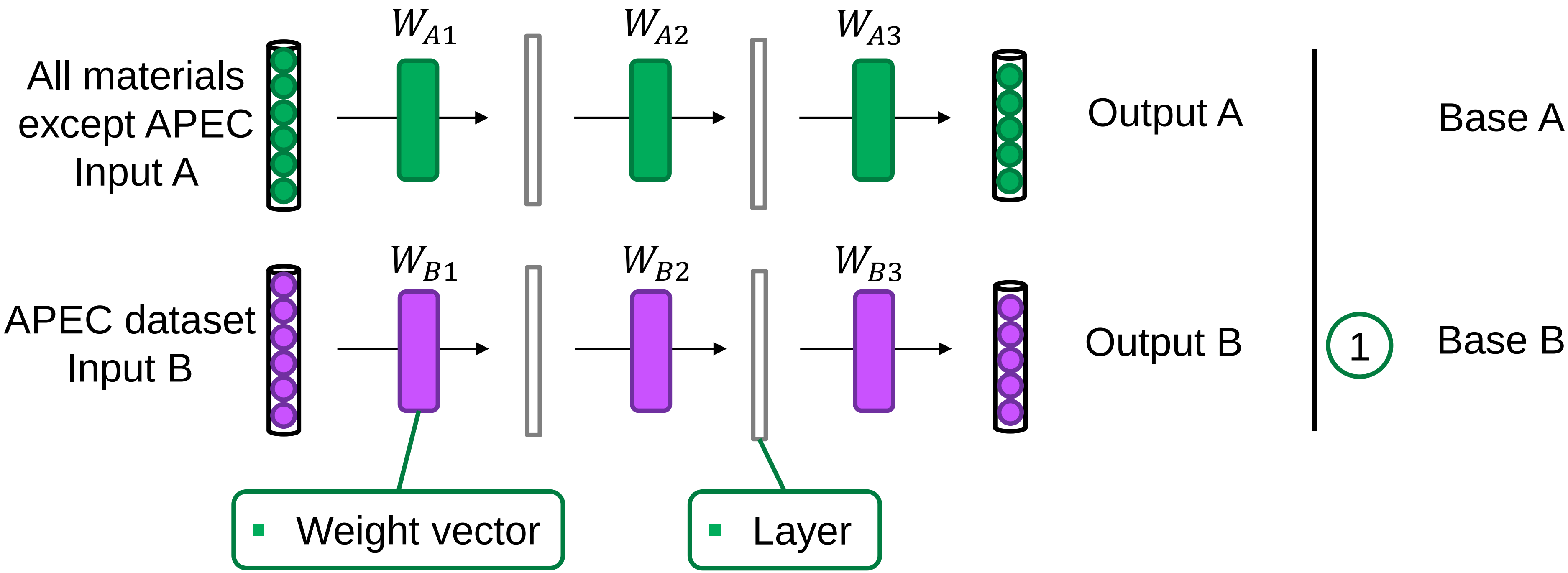
Experiment setup: scenario 1



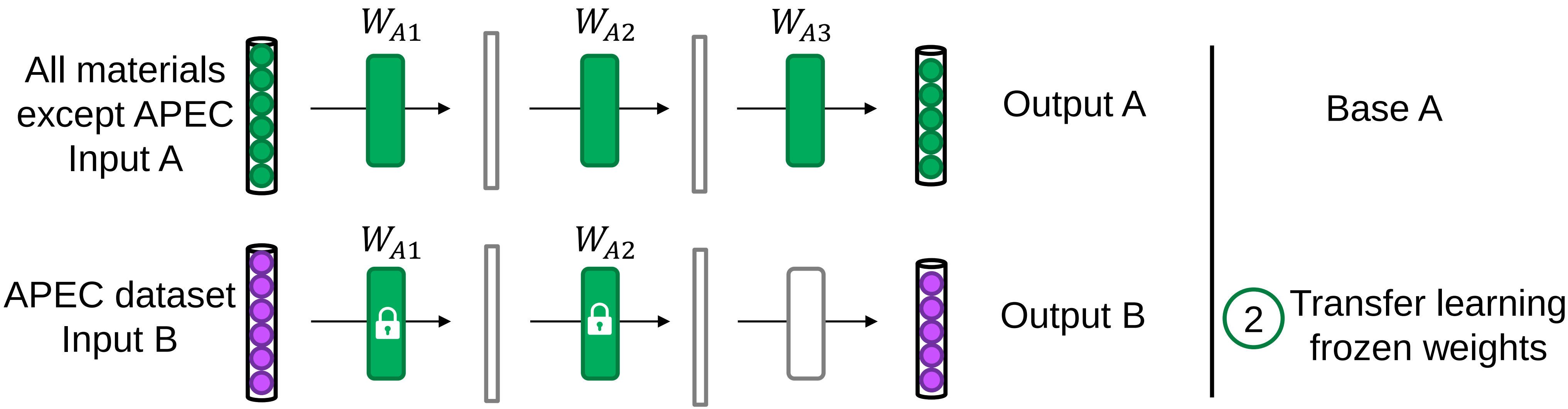
[YCB+14]

Experiment setup: scenario 1



[YCB+14]

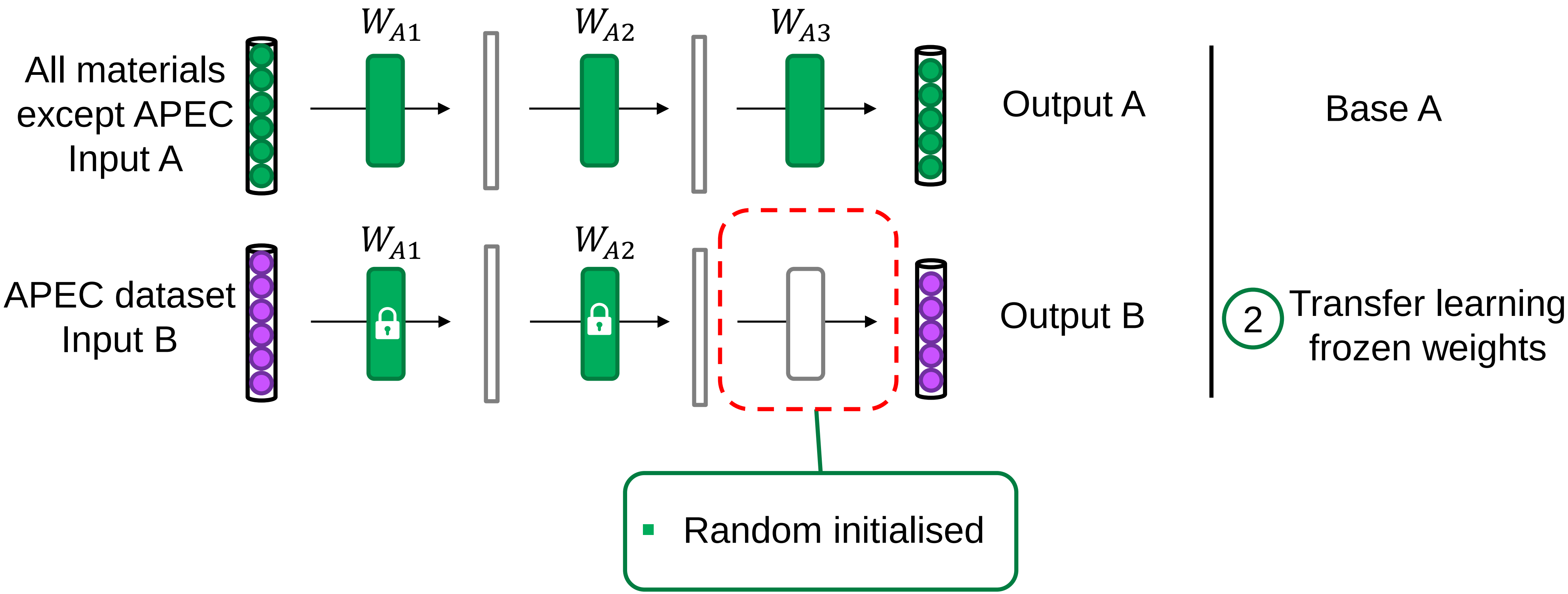
Experiment setup: scenario 2



- To simplify the model, we don't consider ensemble learning but mainly focus on transfer learning, namely DNN-TL model

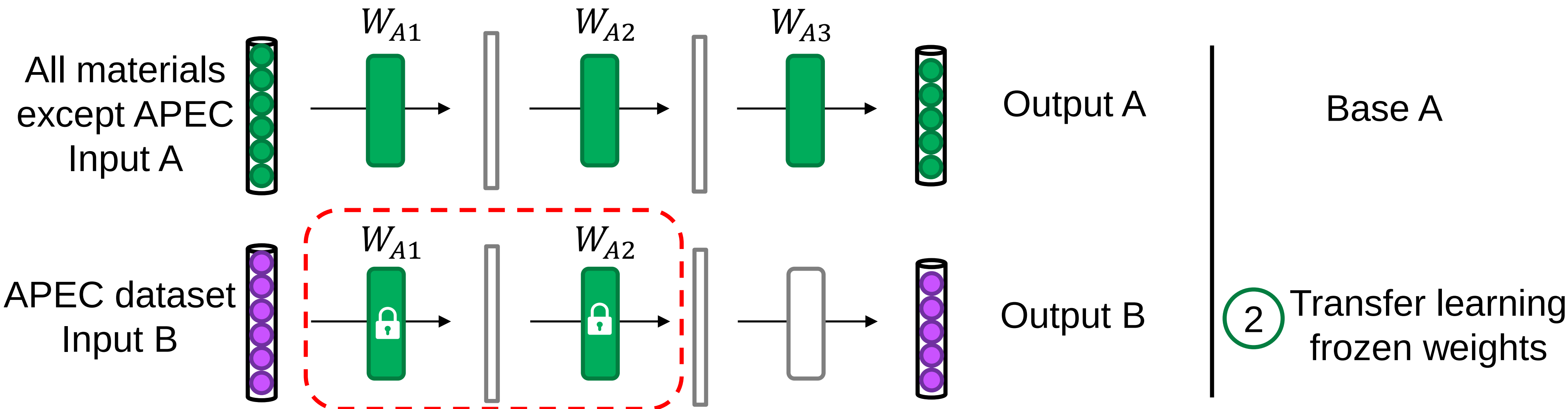
[YCB+14]

Experiment setup: scenario 2



[YCB+14]

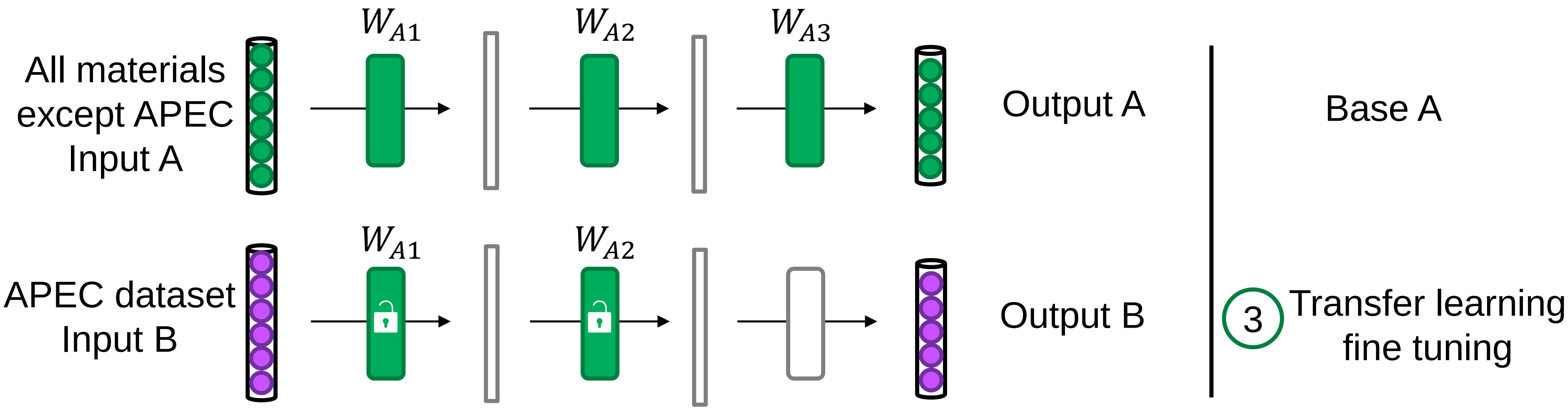
Experiment setup: scenario 2



- Two layers are copied from Base A
- Locked: weights are **not trainable**

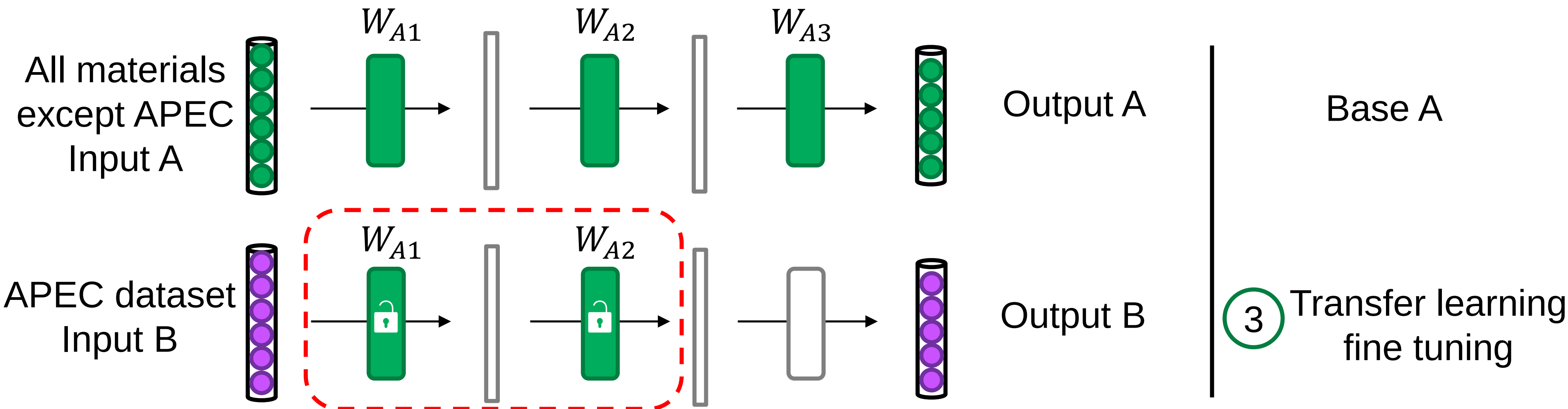
[YCB+14]

Experiment setup: scenario 3



[YCB+14]

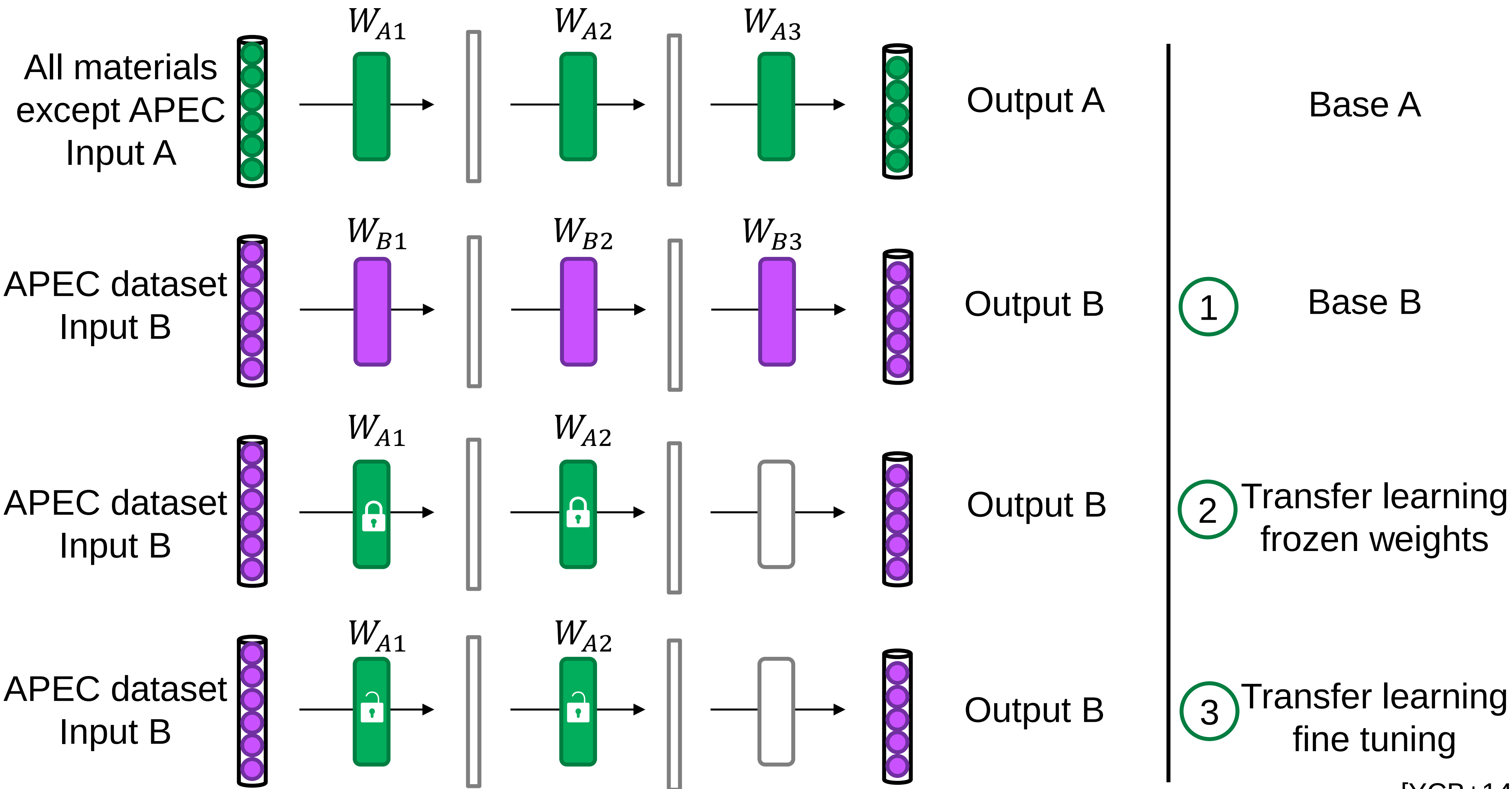
Experiment setup: scenario 3



- Two layers are copied from Base A
- Unlocked: weights are **trainable**

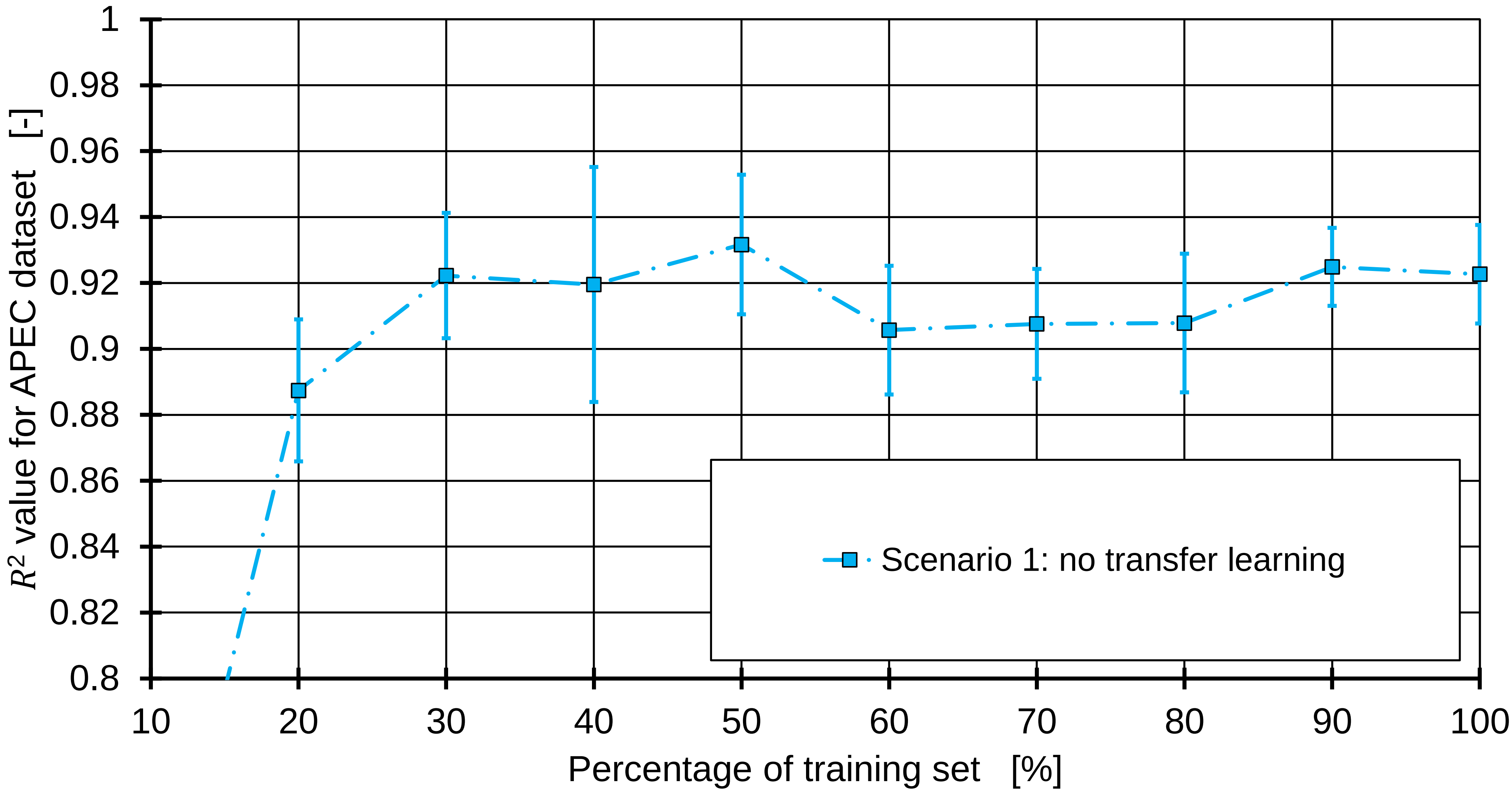
[YCB+14]

Experiment setup overview



[YCB+14]

Effect of the training dataset size on transfer learning



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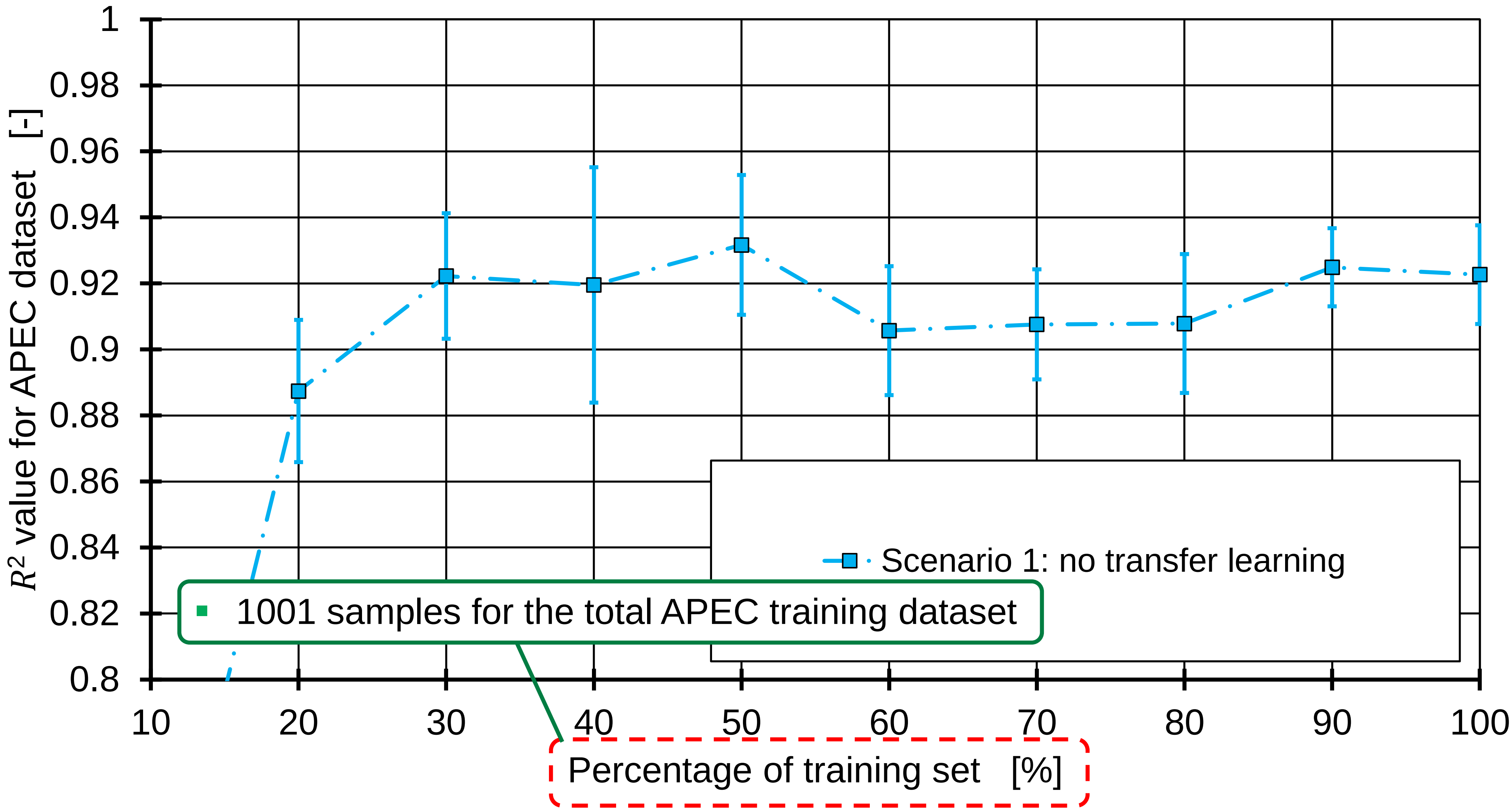

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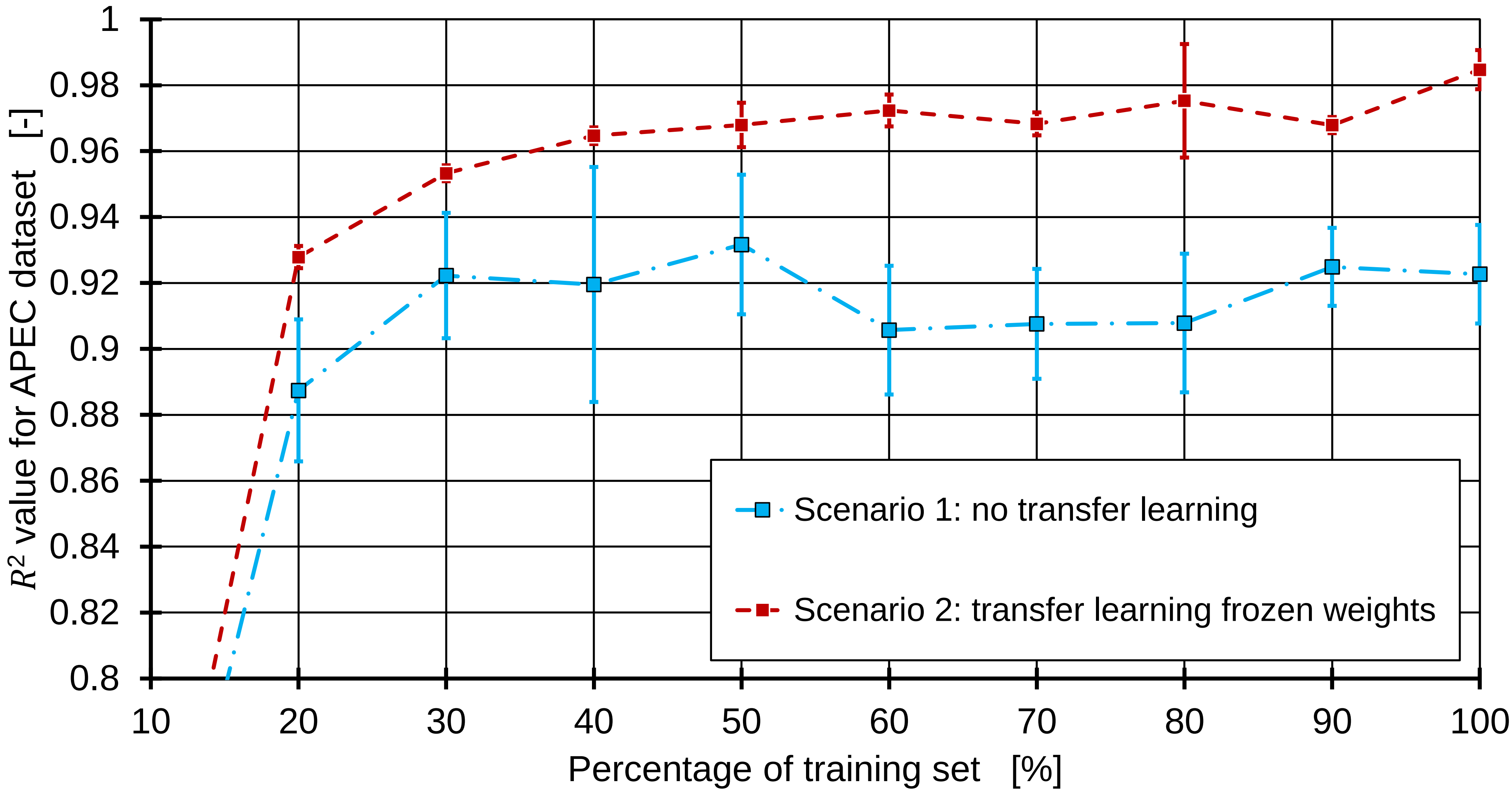

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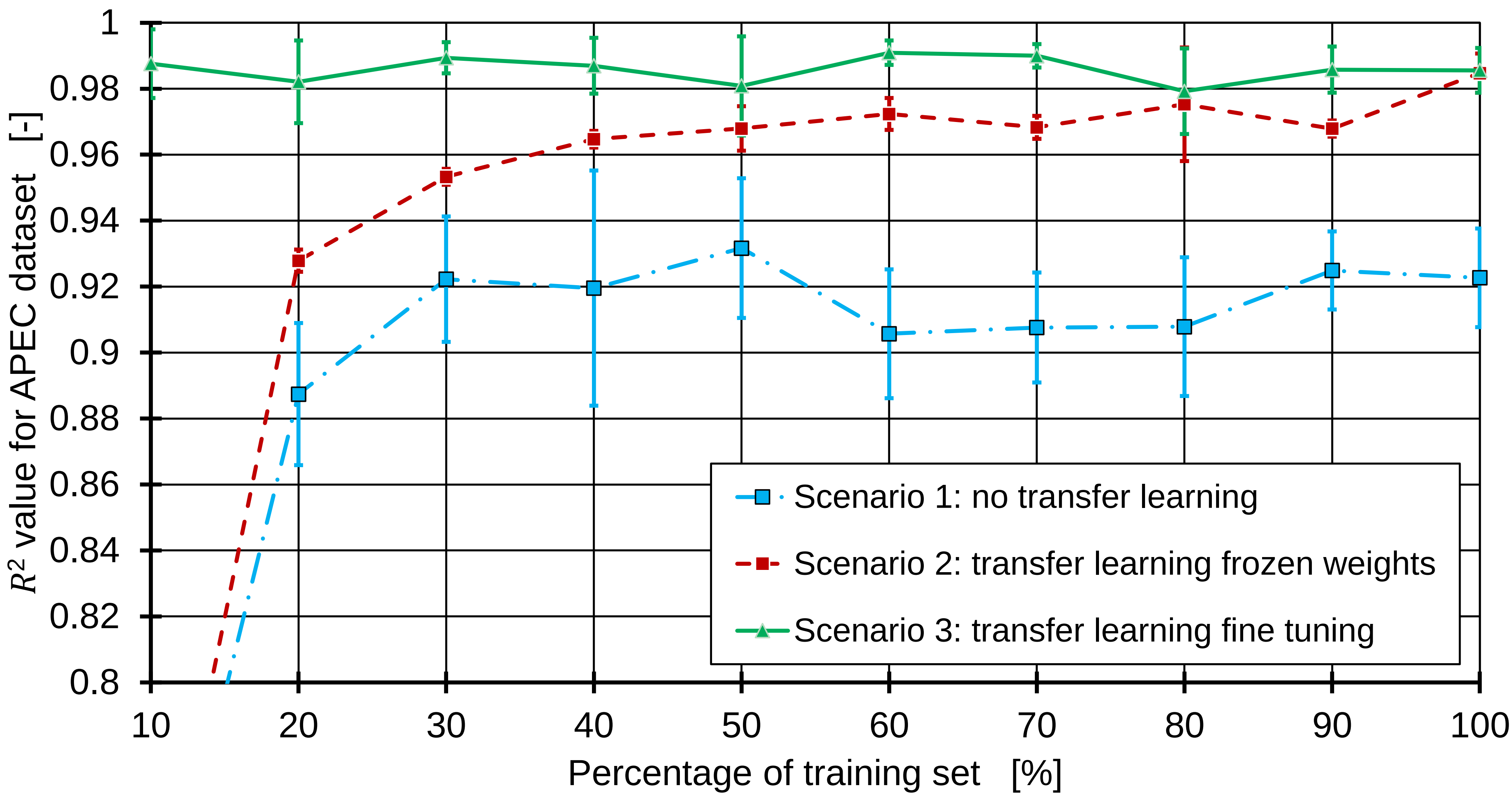

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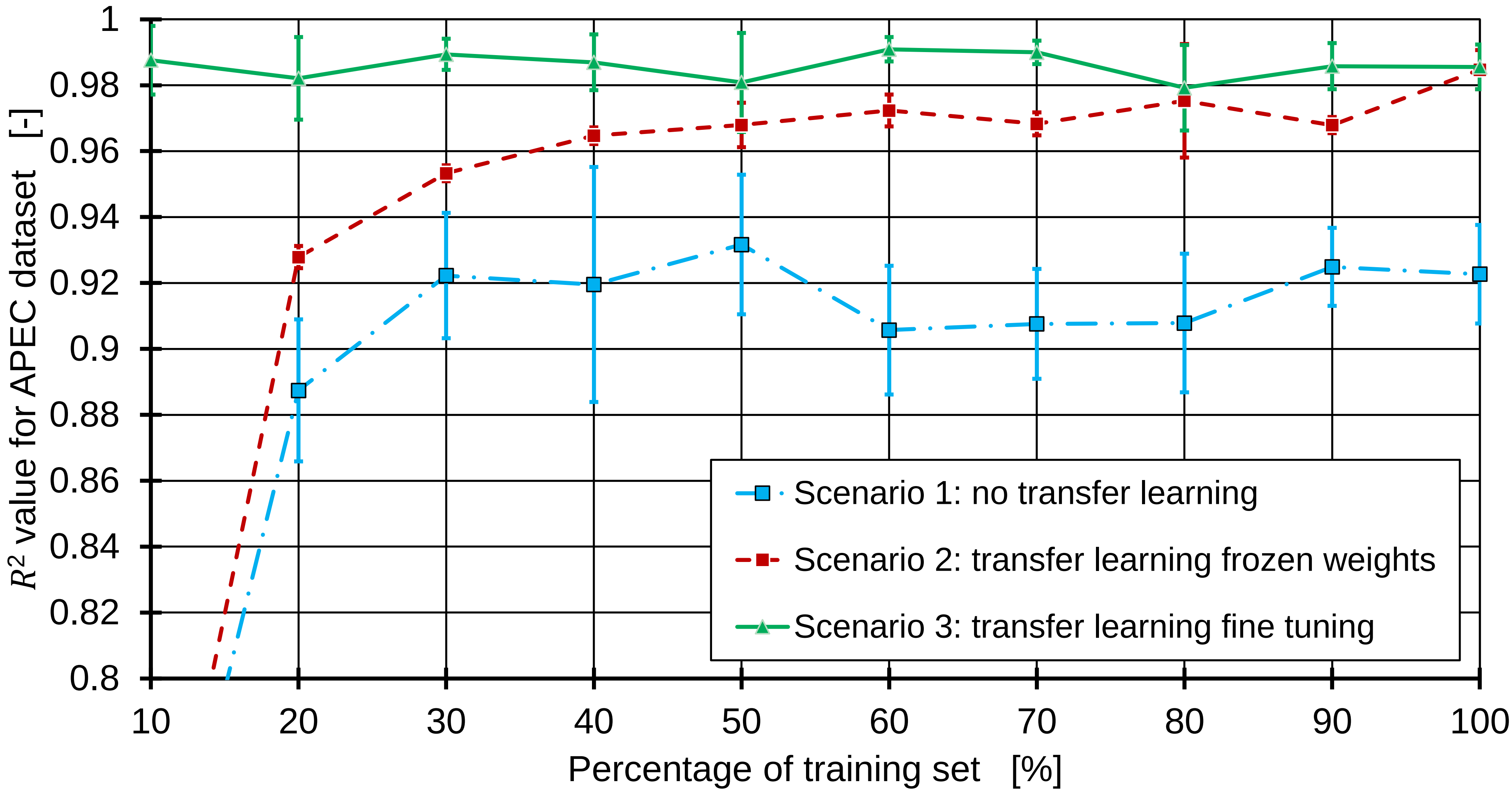
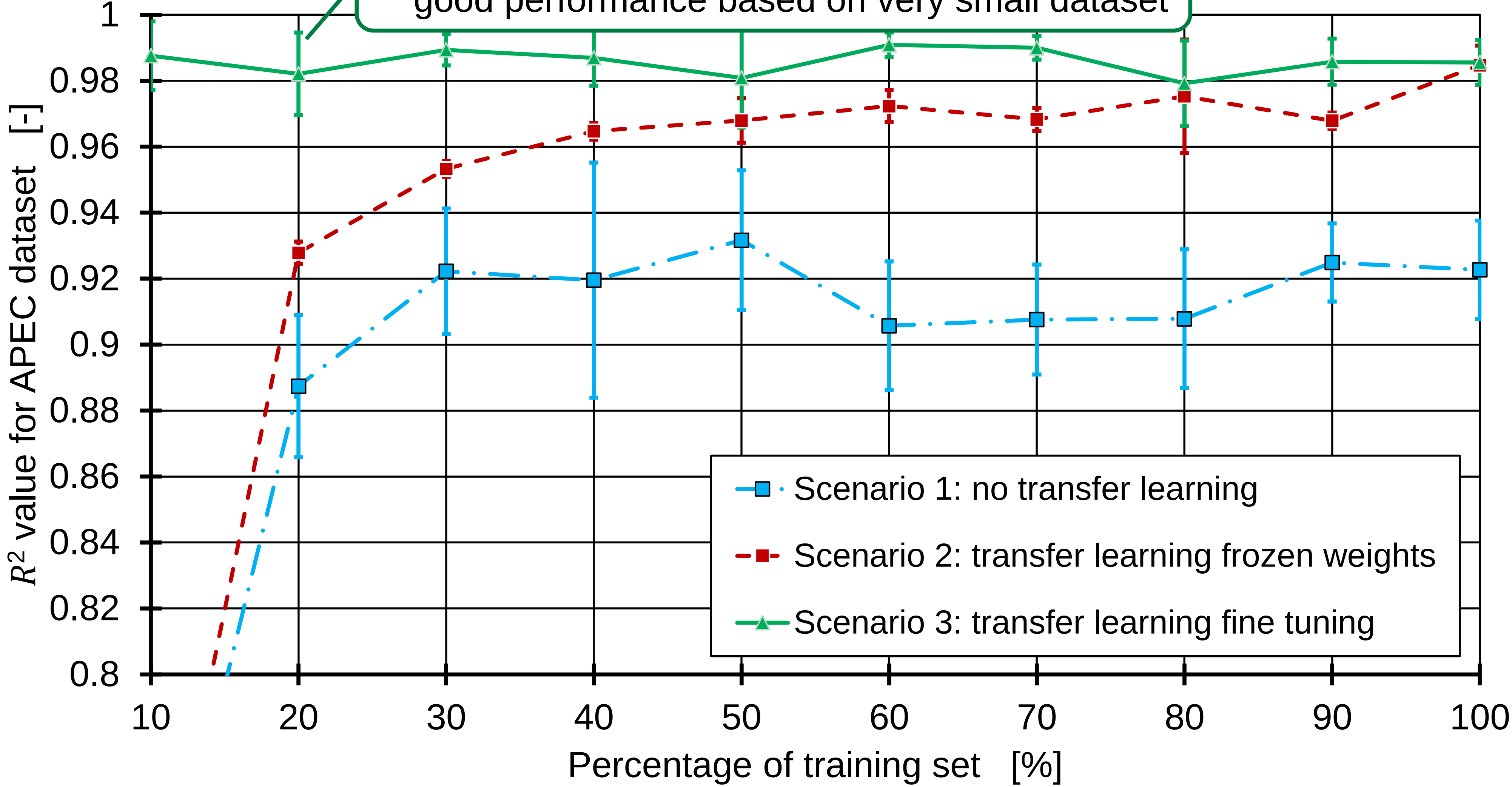


Effect of the training dataset size on transfer learning

- Transfer learning with fine tuning can achieve good performance based on very small dataset



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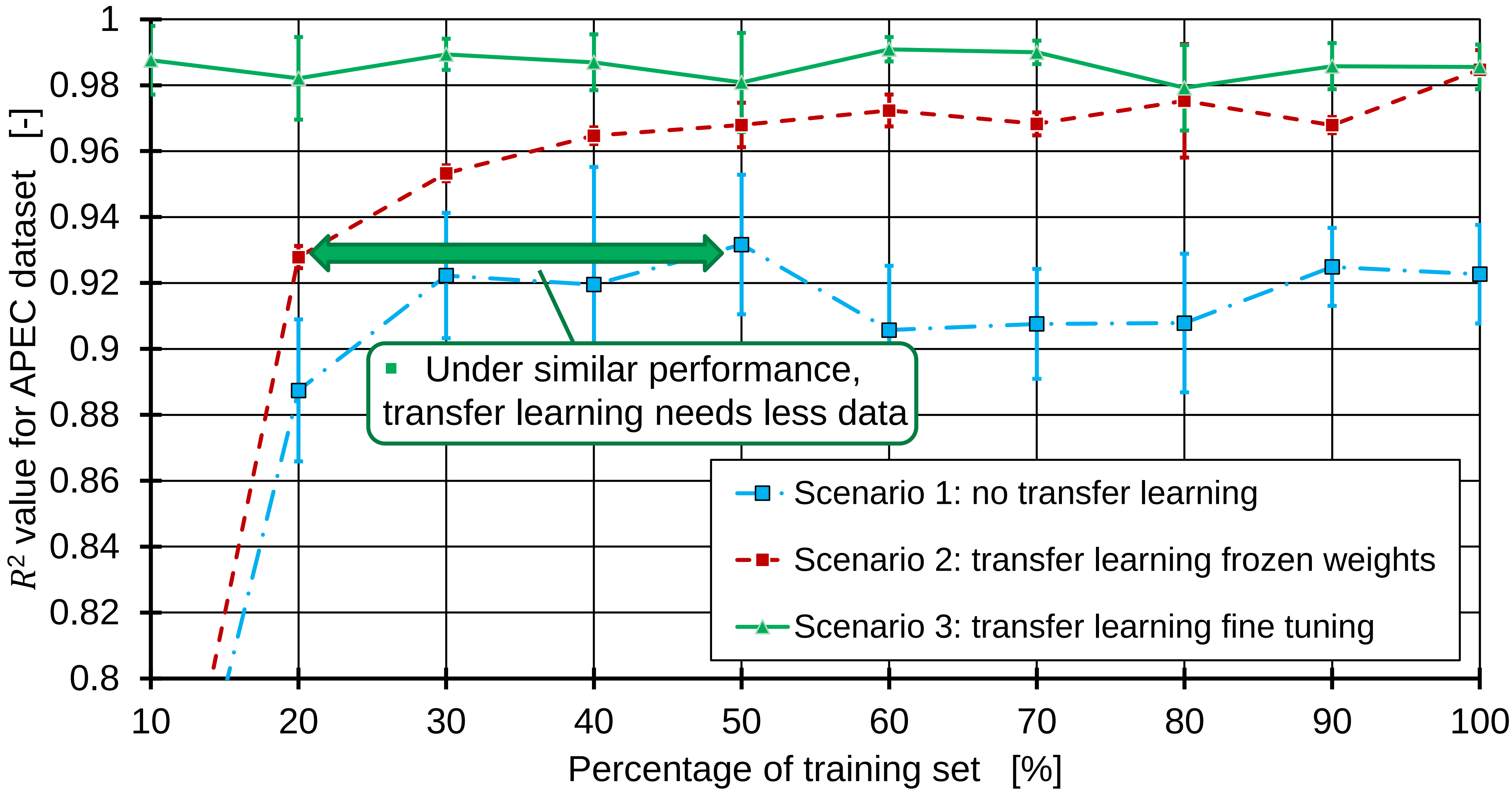

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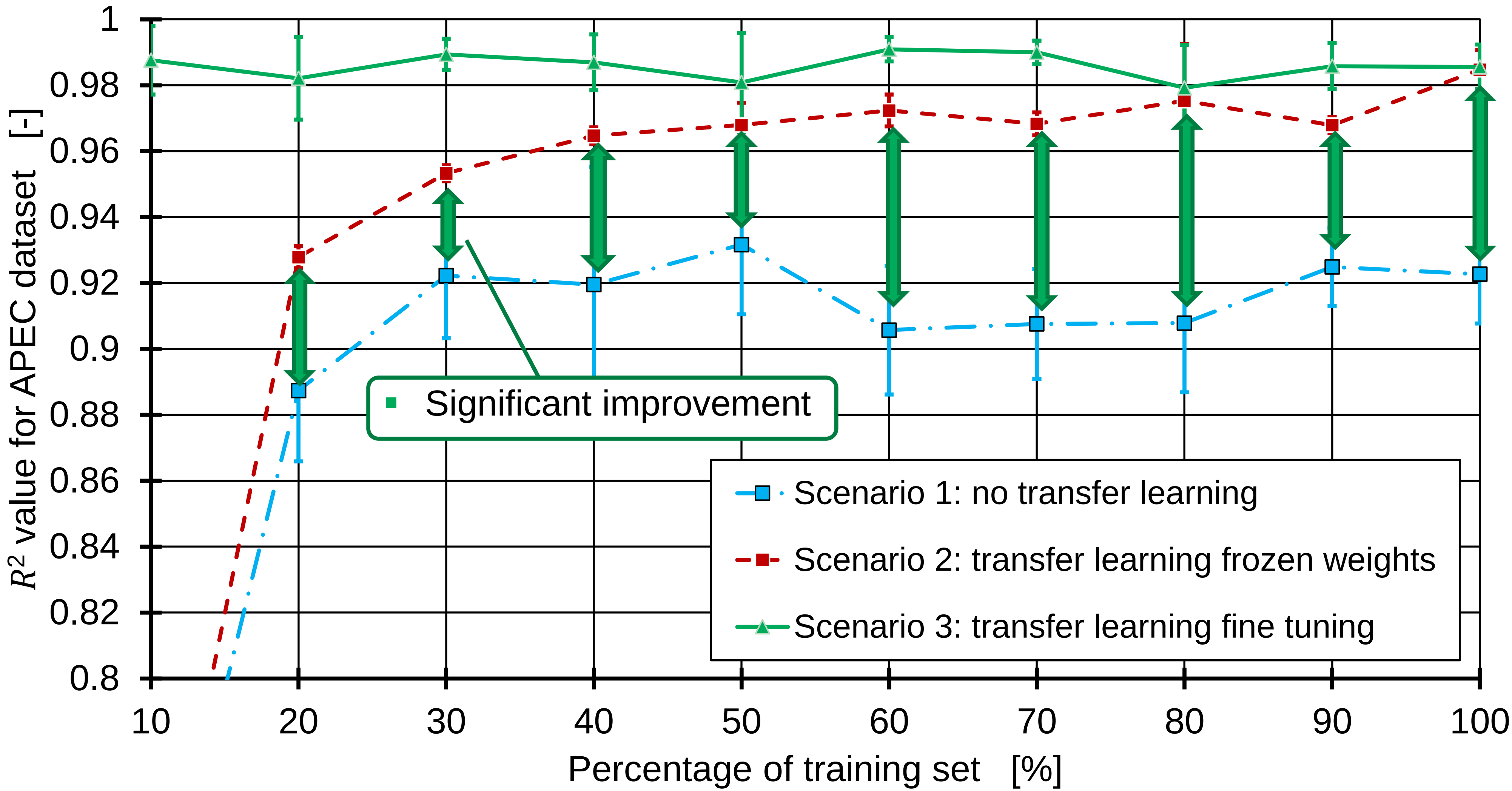
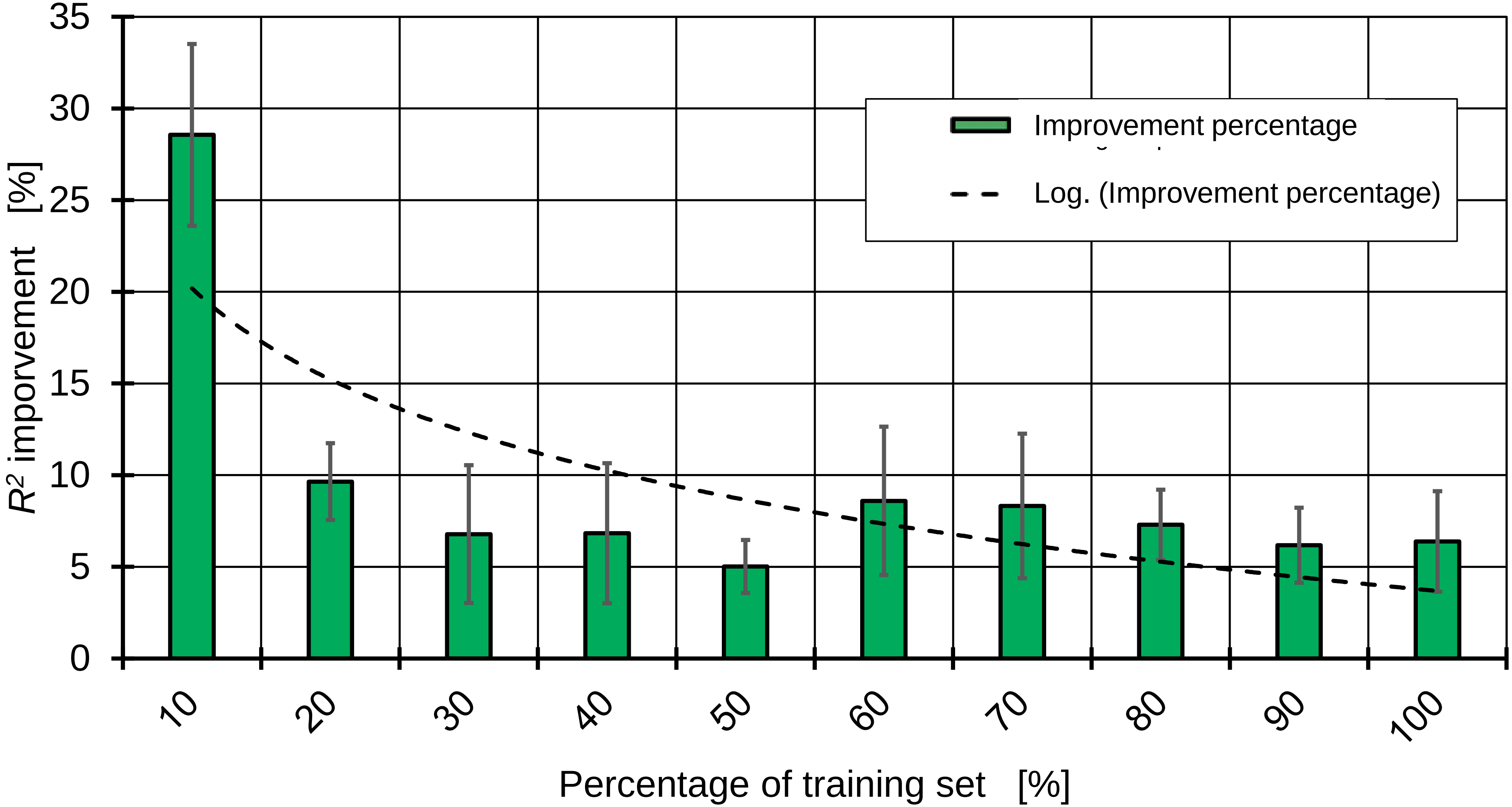


Improvement percentage of R^2 value due to transfer learning



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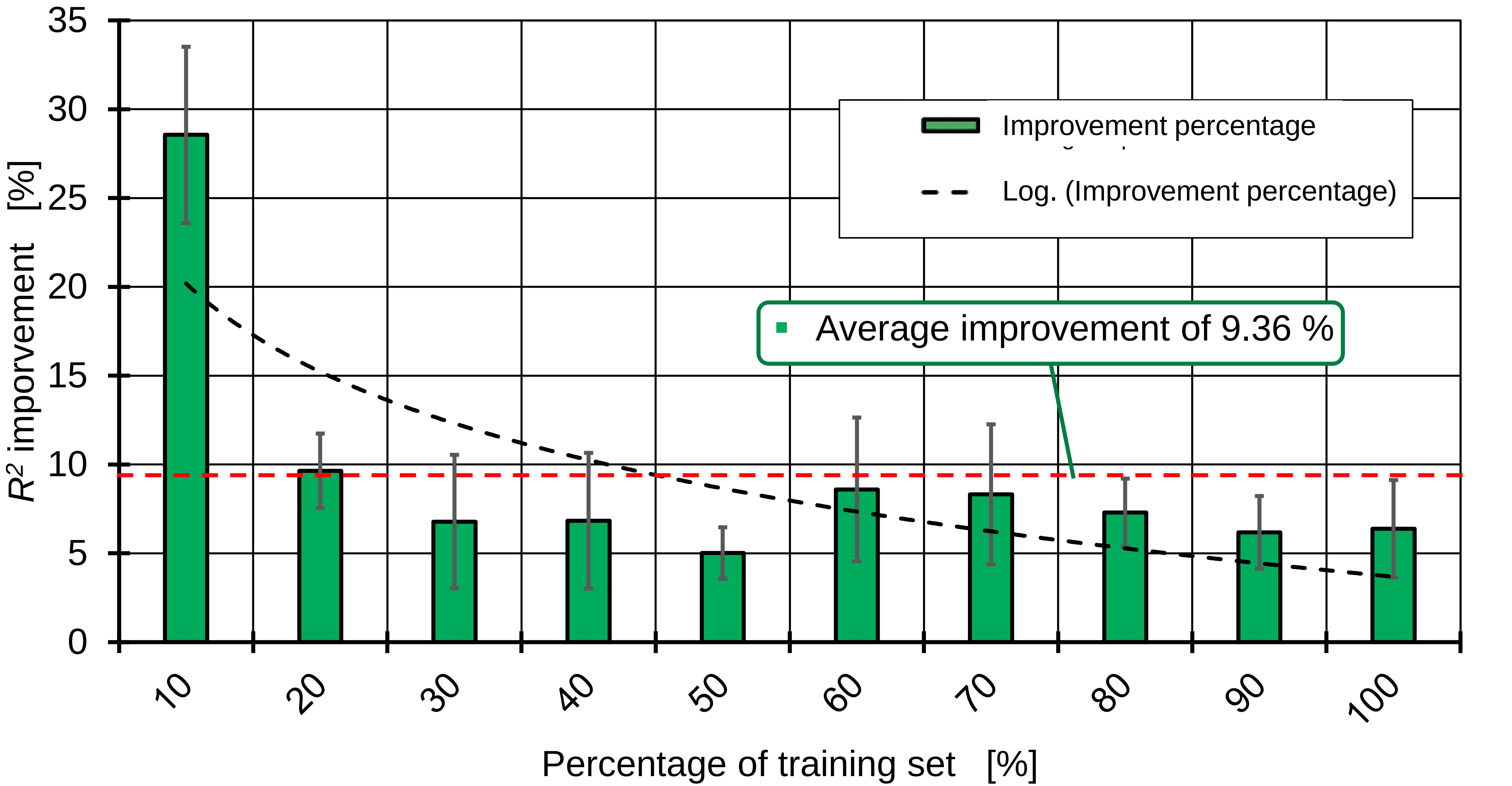

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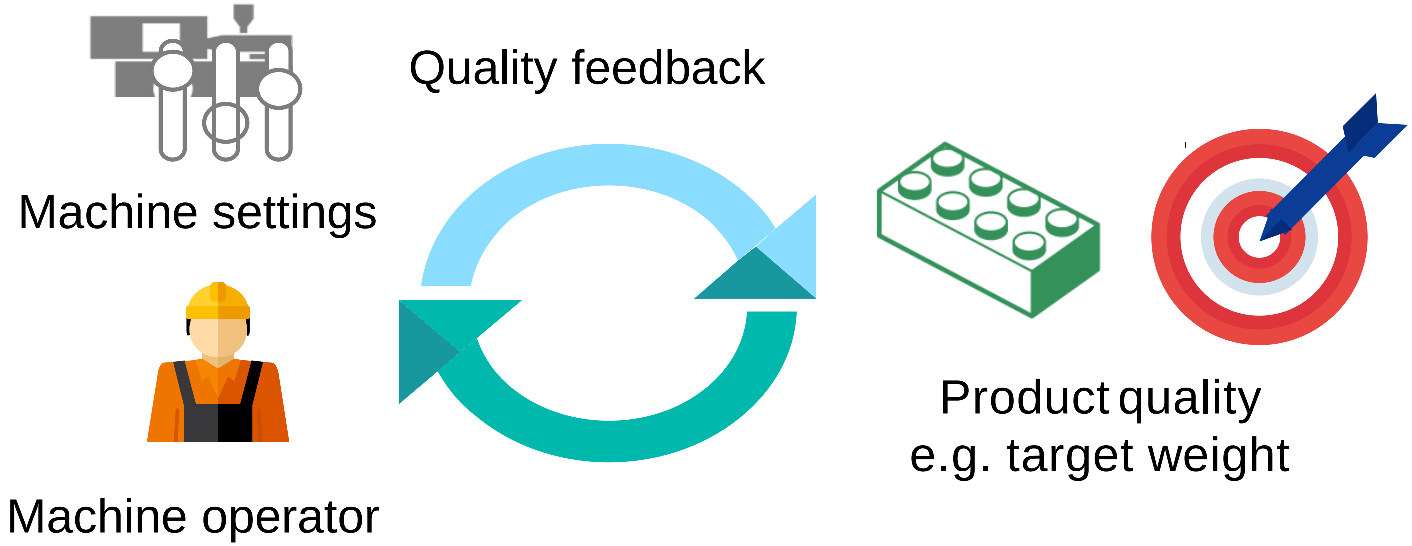
Application in finding best machine settings

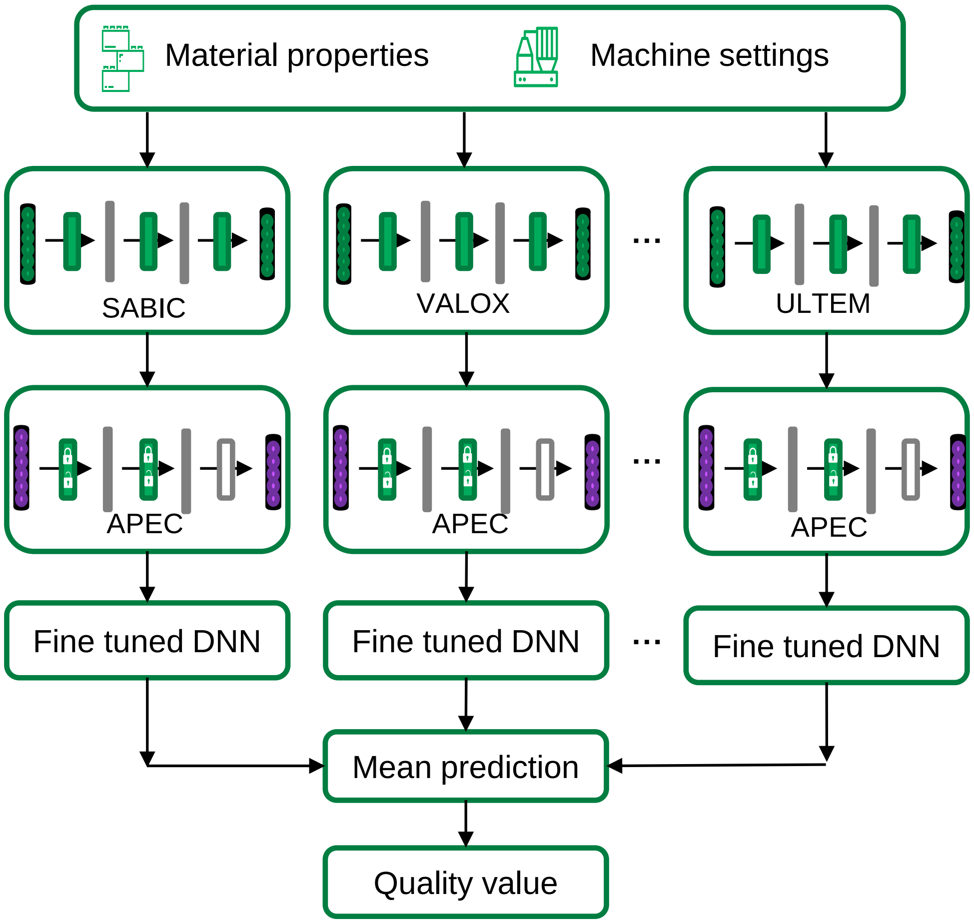


Trial of machine settings based on:

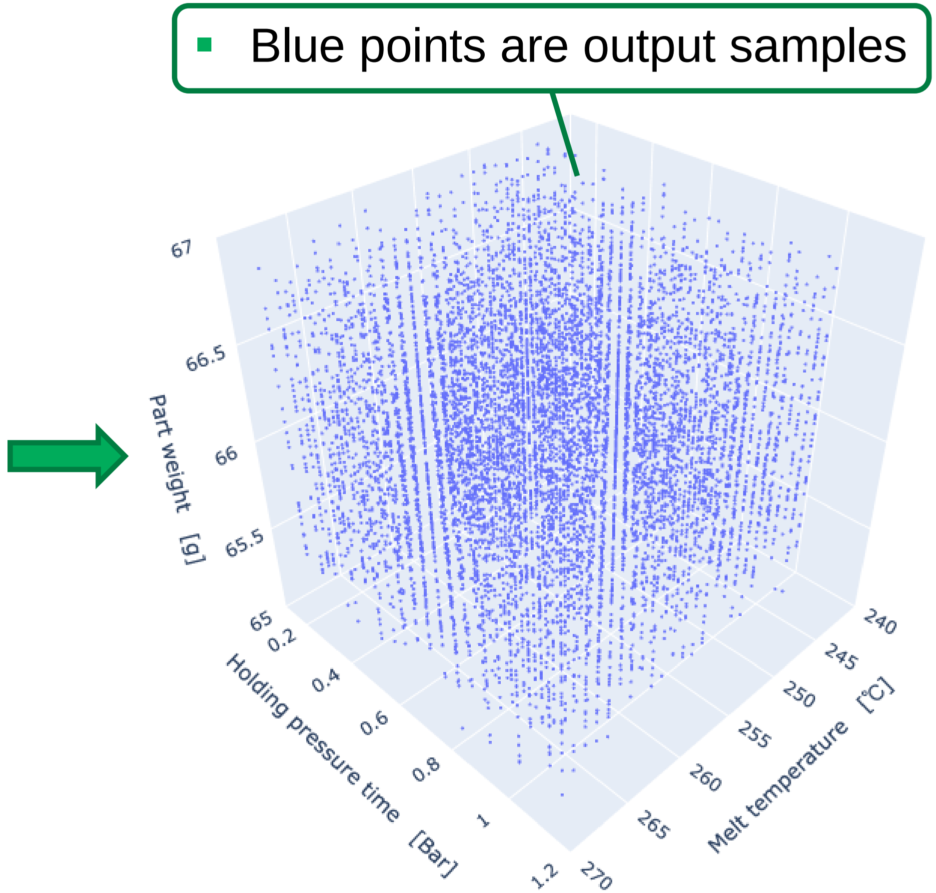
- Recommendations of material supplier
- Experience, intuition of the operator

[Hei17]

Part weight prediction of random machine settings combination

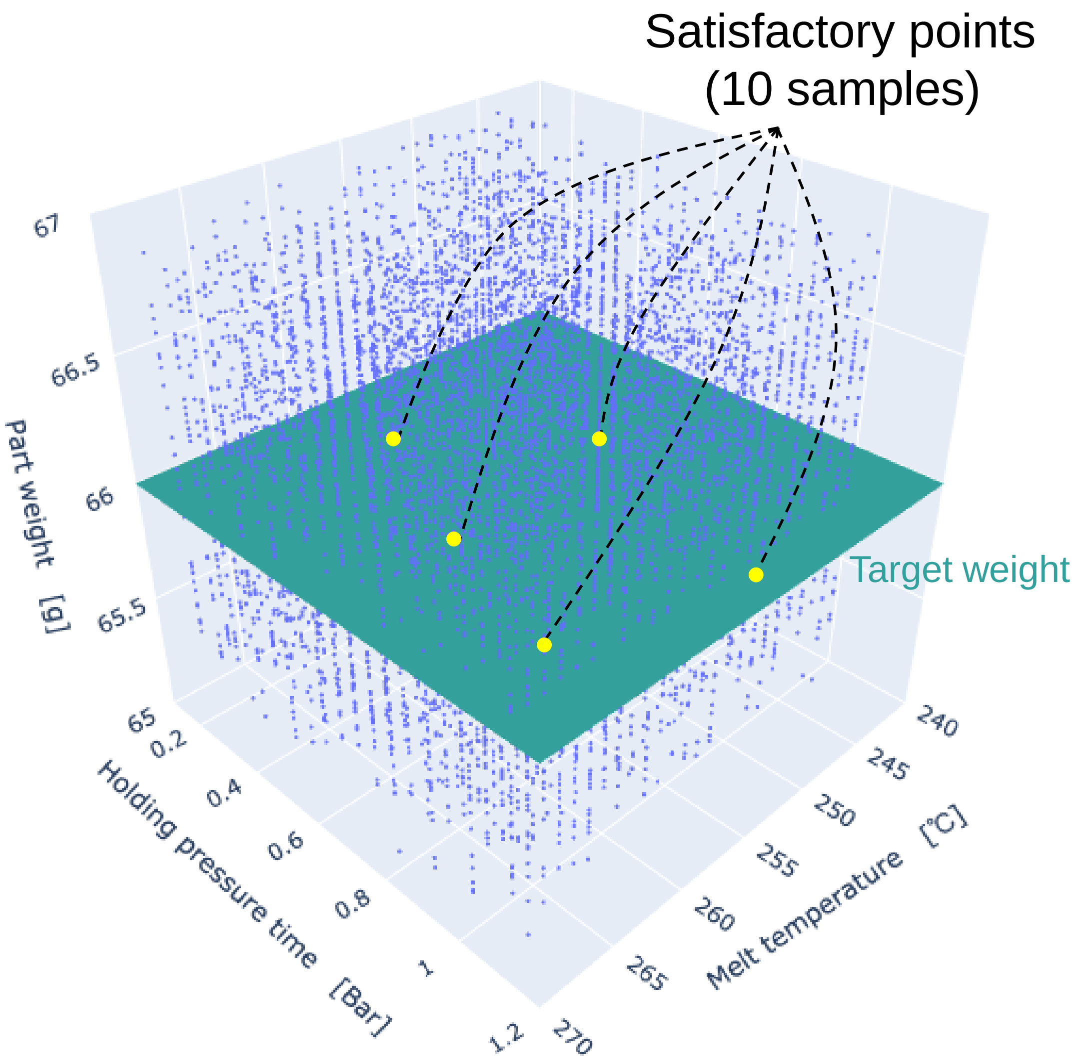


Proposed DNN-ETL model



Prediction result of 10000 samples

Output of process condition recommender system

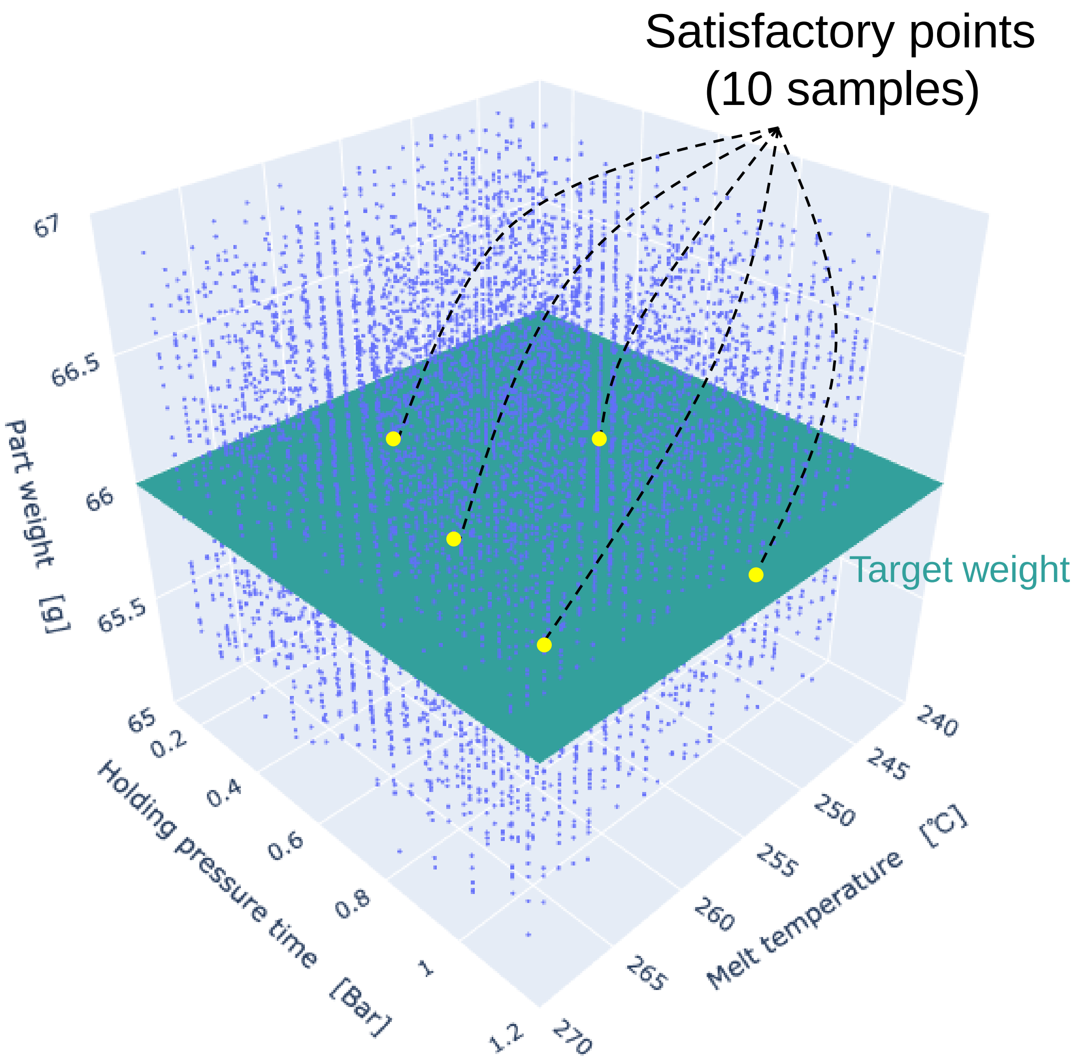


Example experiment

Current machine setting parameters

No.	Melt temp.	Cavity temp.	Press time	Cool time	Flow rate	Hold press
1	245	48	1	1.5	43	490

Output of process condition recommender system



Example experiment

Current machine setting parameters

No.	Melt temp.	Cavity temp.	Press time	Cool time	Flow rate	Hold press
1	245	48	1	1.5	43	490

Calculate distance

Final recommend conditions

No.	Melt temp.	Cavity temp.	Press time	Cool time	Flow rate	Hold press
1	246	67	0.2	1.8	32	480
2	249	64	0.2	2	49	610
3	245	42	0.7	2.4	44	480
⋮	⋮	⋮	⋮	⋮	⋮	⋮
10	245	55	1.1	1.9	53	600

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[URL00]

Conclusion and outlook

Develop DNN-ETL model

R^2 test score is 0.9207 and it surpasses the state-of-the-art performance of 0.90 [TGH+18]

Analyse the improvement due to transfer learning

An average improvement of 9.36 % of R^2 value can be achieved compared to DNN without transfer learning.

Apply feature ranking method

Five most important features: solid density, holding pressure, thermal conductivity, no flow temperature and ejection temperature

Conclusion and outlook

Develop DNN-ETL model

R^2 test score is 0.9207 and it surpasses the state-of-the-art performance of 0.90 [TGH+18]

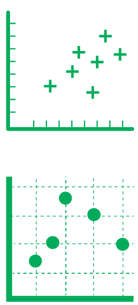
Analyse the improvement due to transfer learning

An average improvement of 9.36 % of R^2 value can be achieved compared to DNN without transfer learning.

Apply feature ranking method

Five most important features: solid density, holding pressure, thermal conductivity, no flow temperature and ejection temperature

Two datasets with same feature space



“when to transfer”

“what to transfer”

?

Conclusion and outlook

Develop DNN-ETL model

R^2 test score is 0.9207 and it surpasses the state-of-the-art performance of 0.90 [TGH+18]

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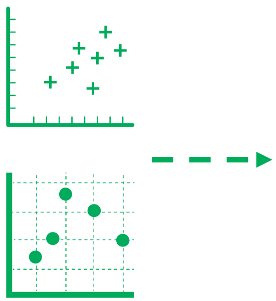

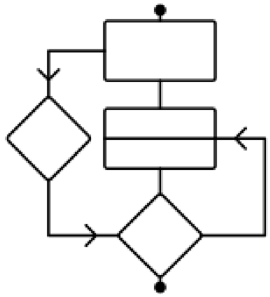

Algorithms

- Test whether the marginal distributions of two domains are similar

Das Institut für Kunststoffverarbeitung
Nachwuchs. Netzwerk. Innovationen.

Thank you for your attention.

I am happy to answer your questions.

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E-Mail: weibo.zhao@rwth-aachen.de

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- [URL01]: N.N.: *PLEXIGLAS Zuschnitt nach Maß. URL: https://kunststoffplattenonline.de/plexiglas/, 24.09.2020*
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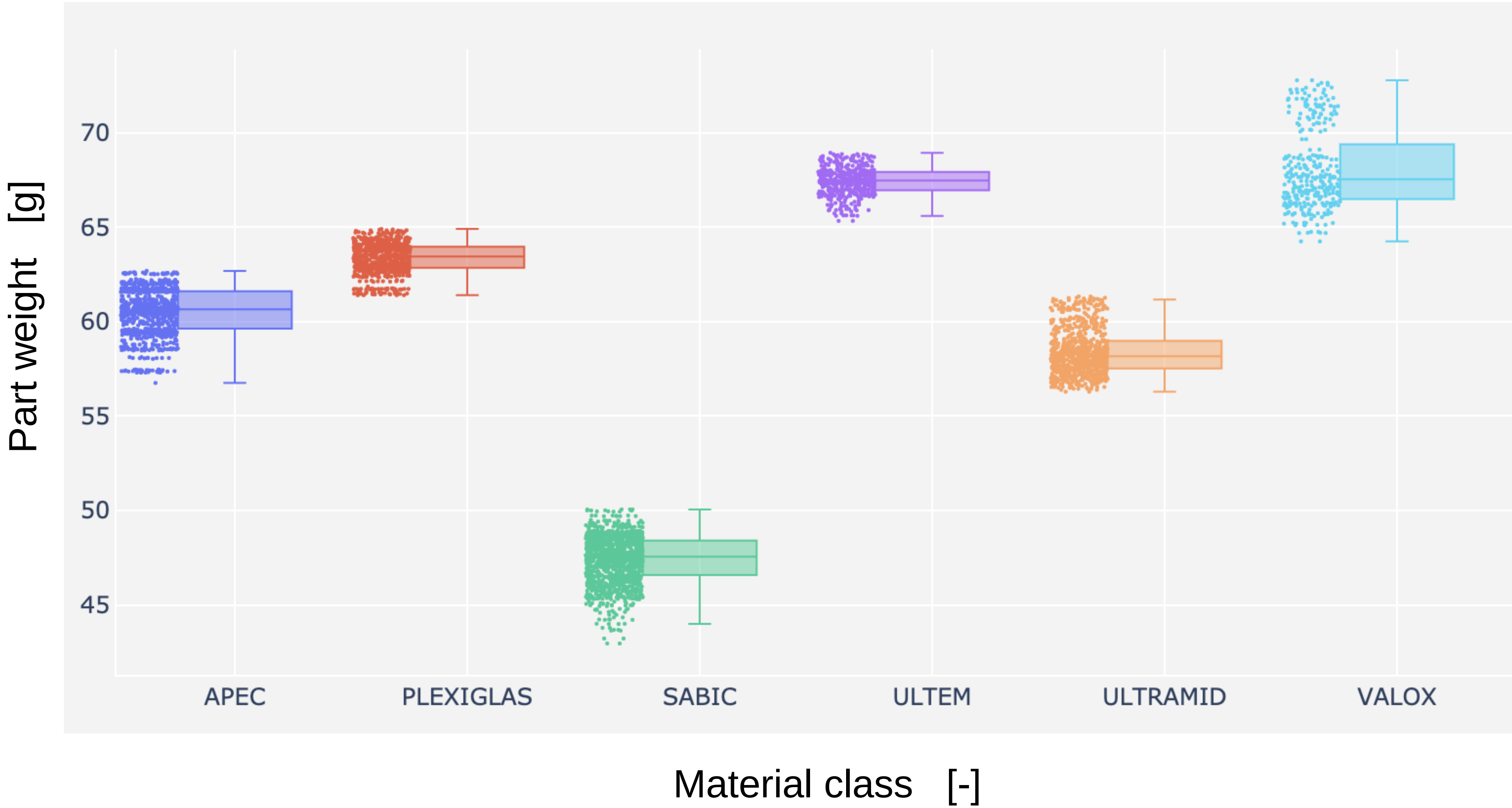
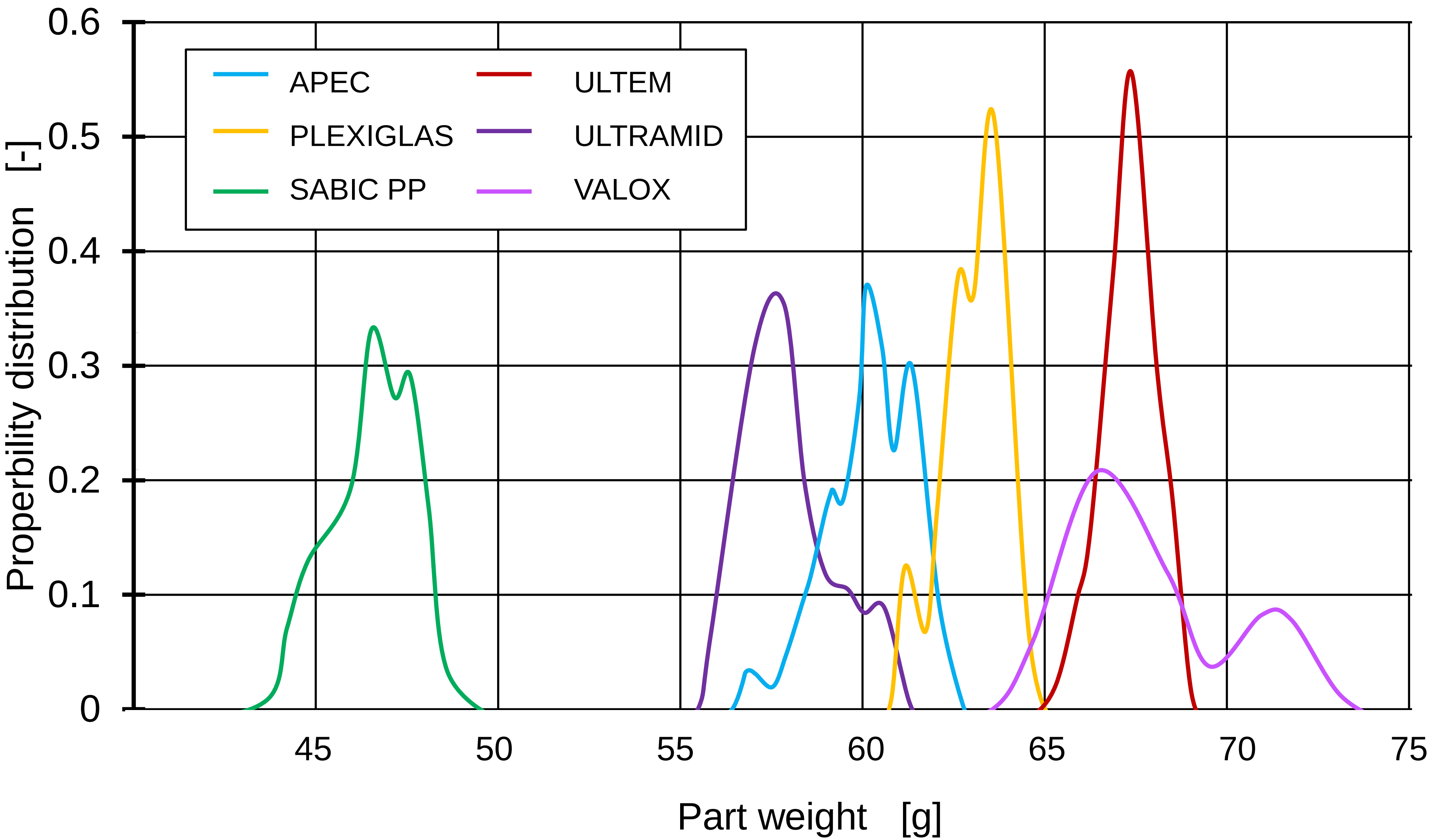
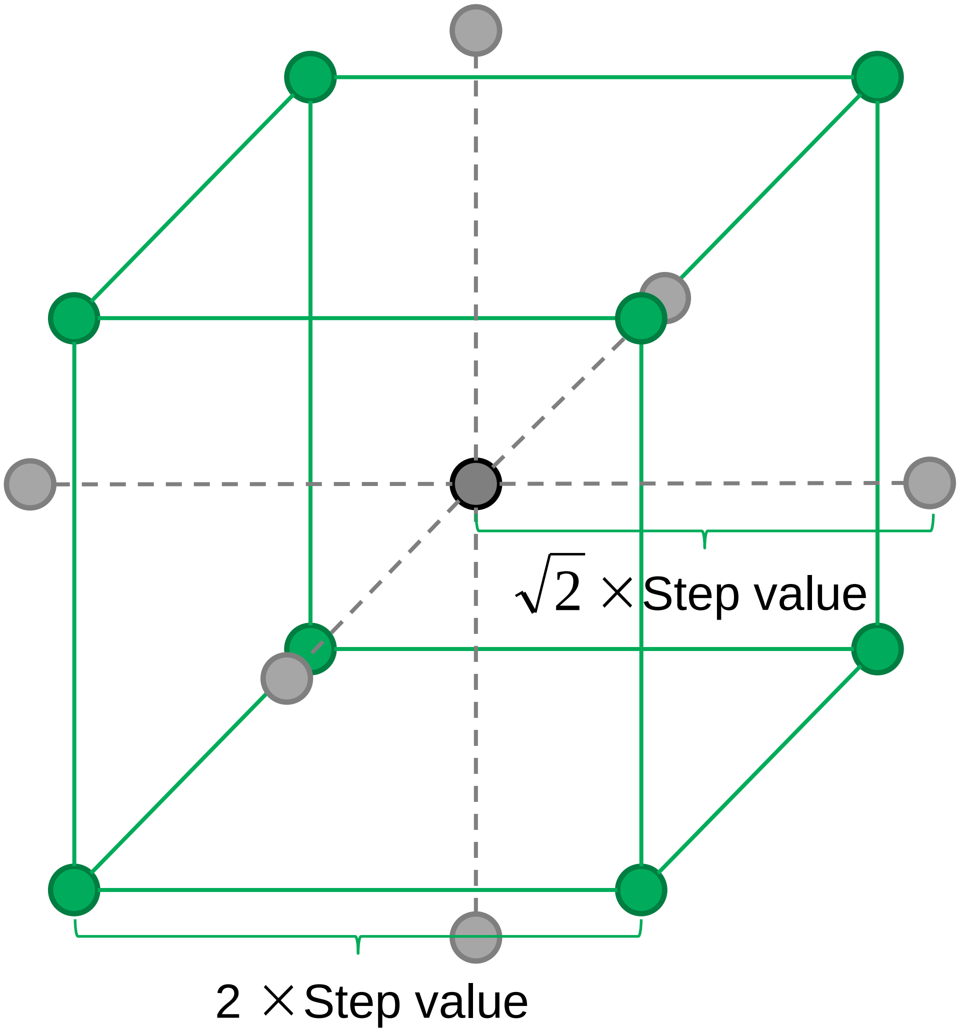
Data visualization of the part weight of the six material classes

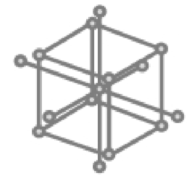


Different part weight distribution of six material classes



Qualitative depiction of 2^n-Experiment (n=3) plan including star and center point



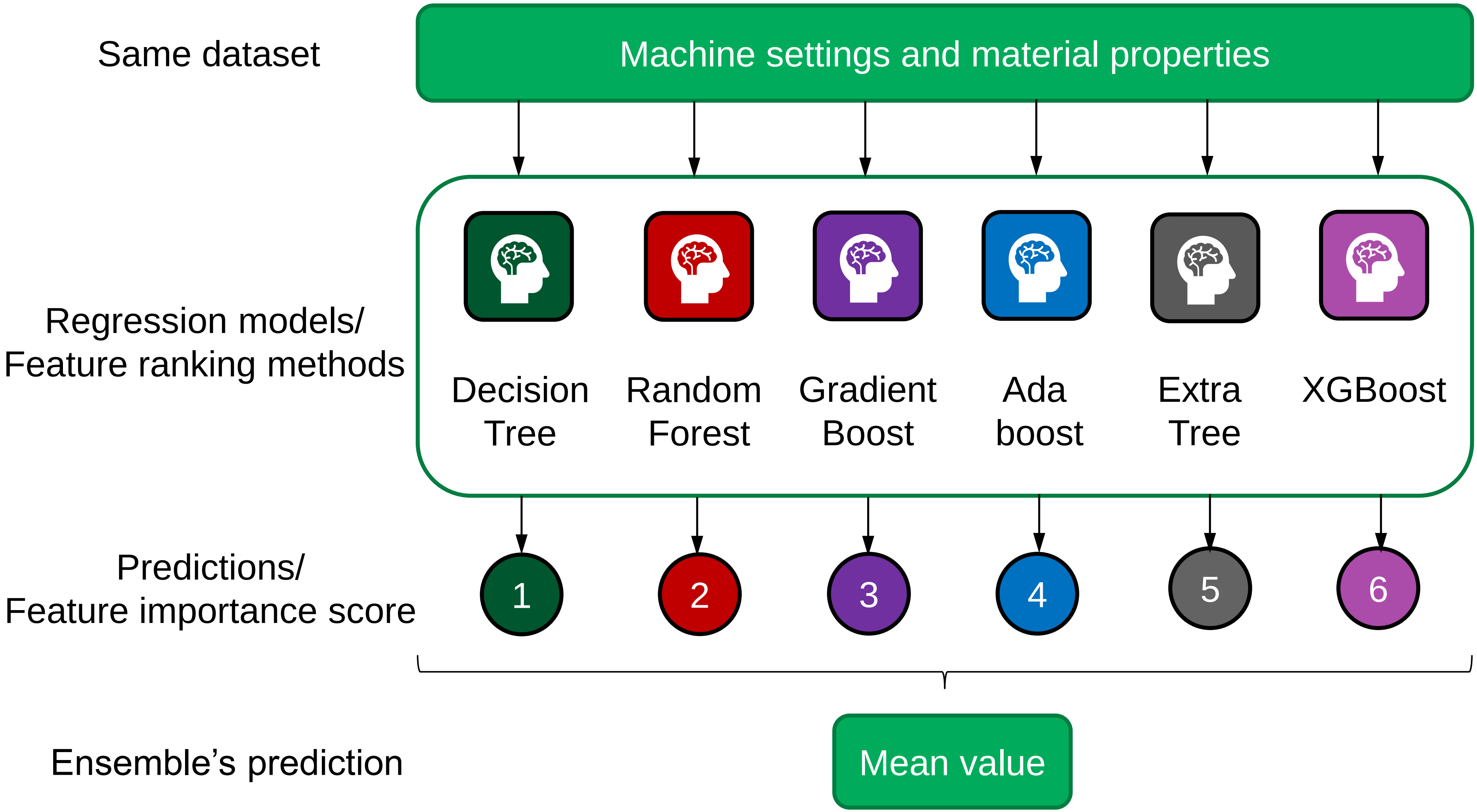


- 77 times of Machine settings combination

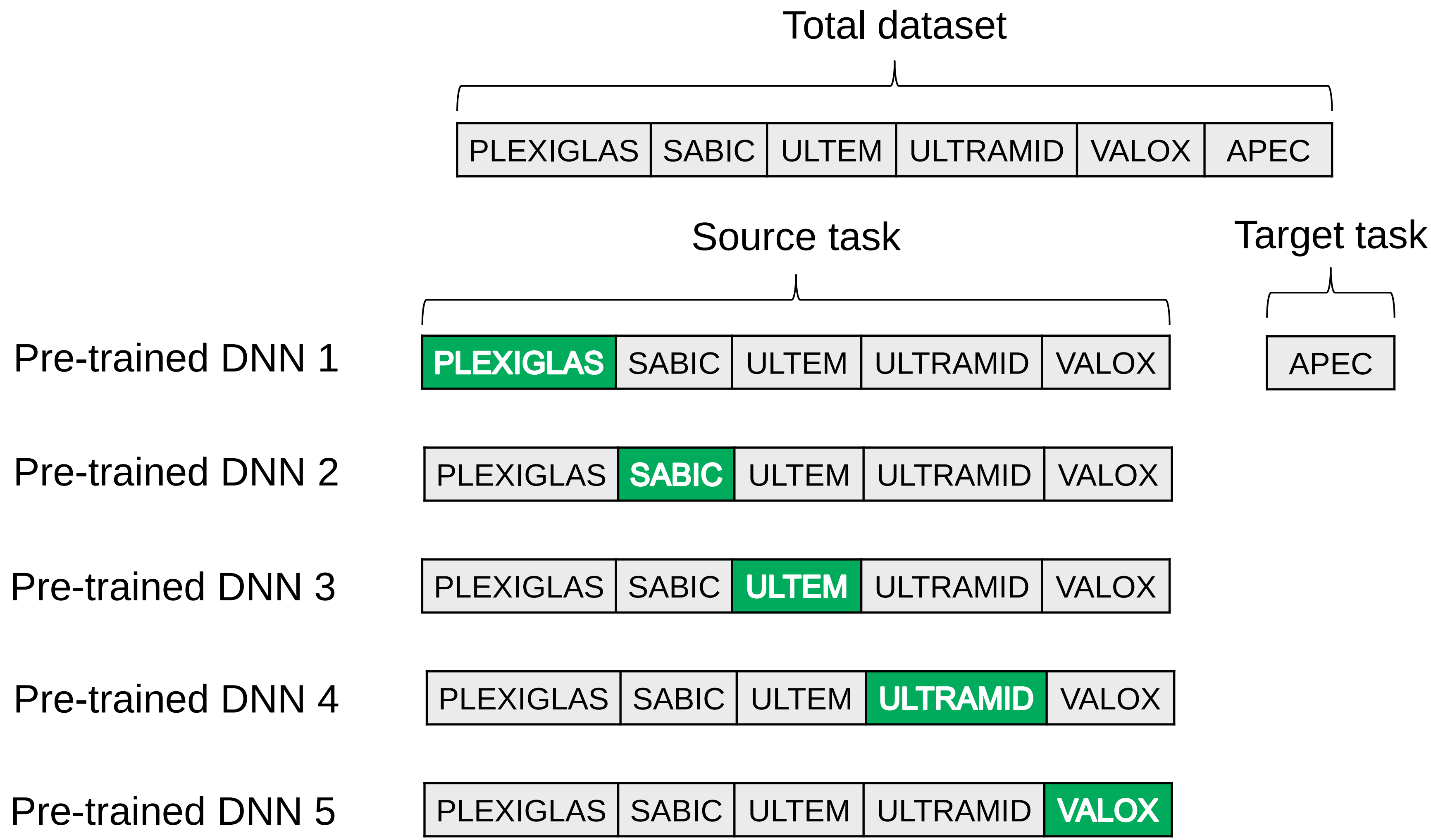
Central composite design (CCD) of experiments:

- Full-factorial experimental design (64-point cube) 2^6
- Star points outside the cube (12 points)
- Central point

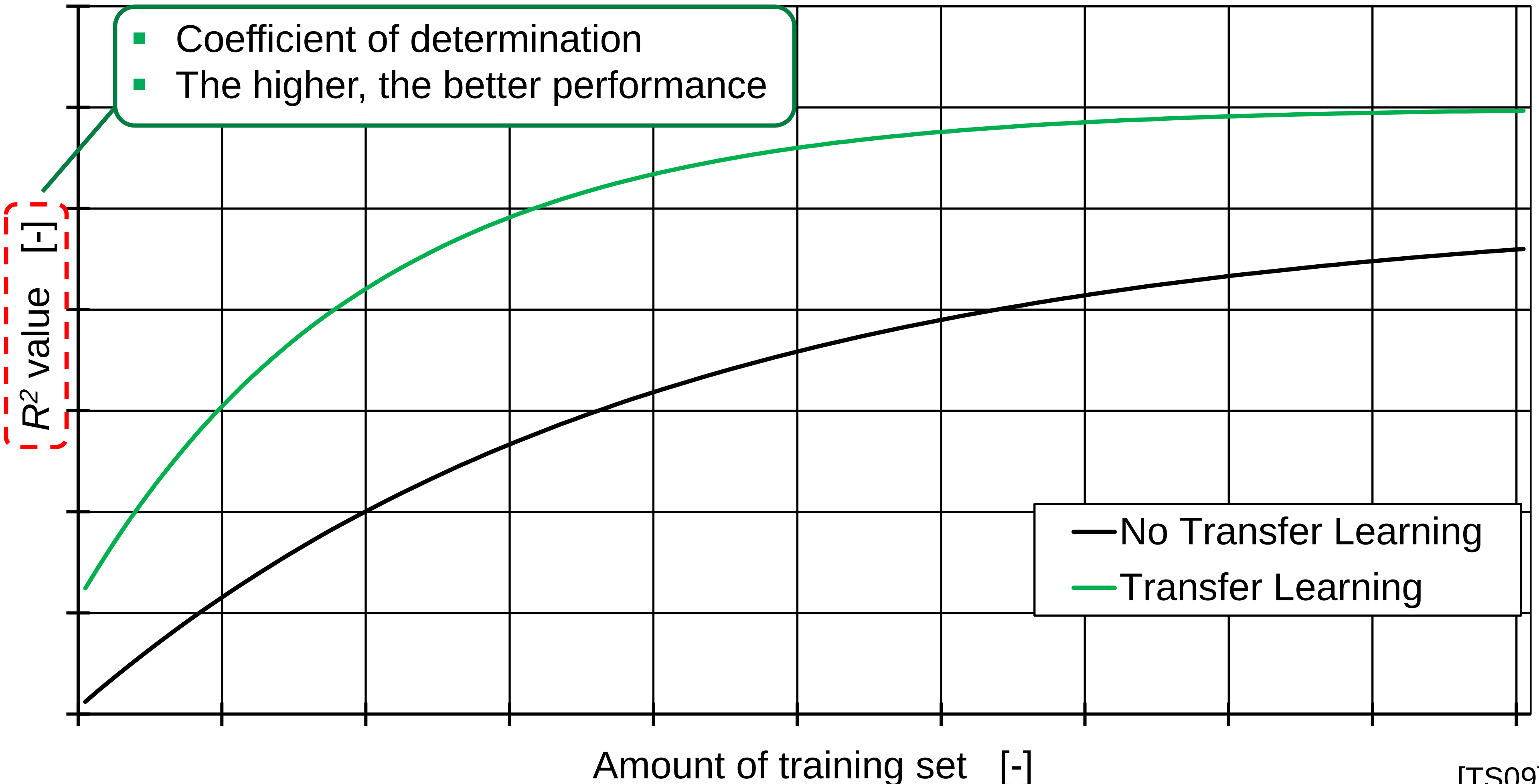
Feature ranking by ensemble learning method



Splitting source dataset into 5 folds according to material classes

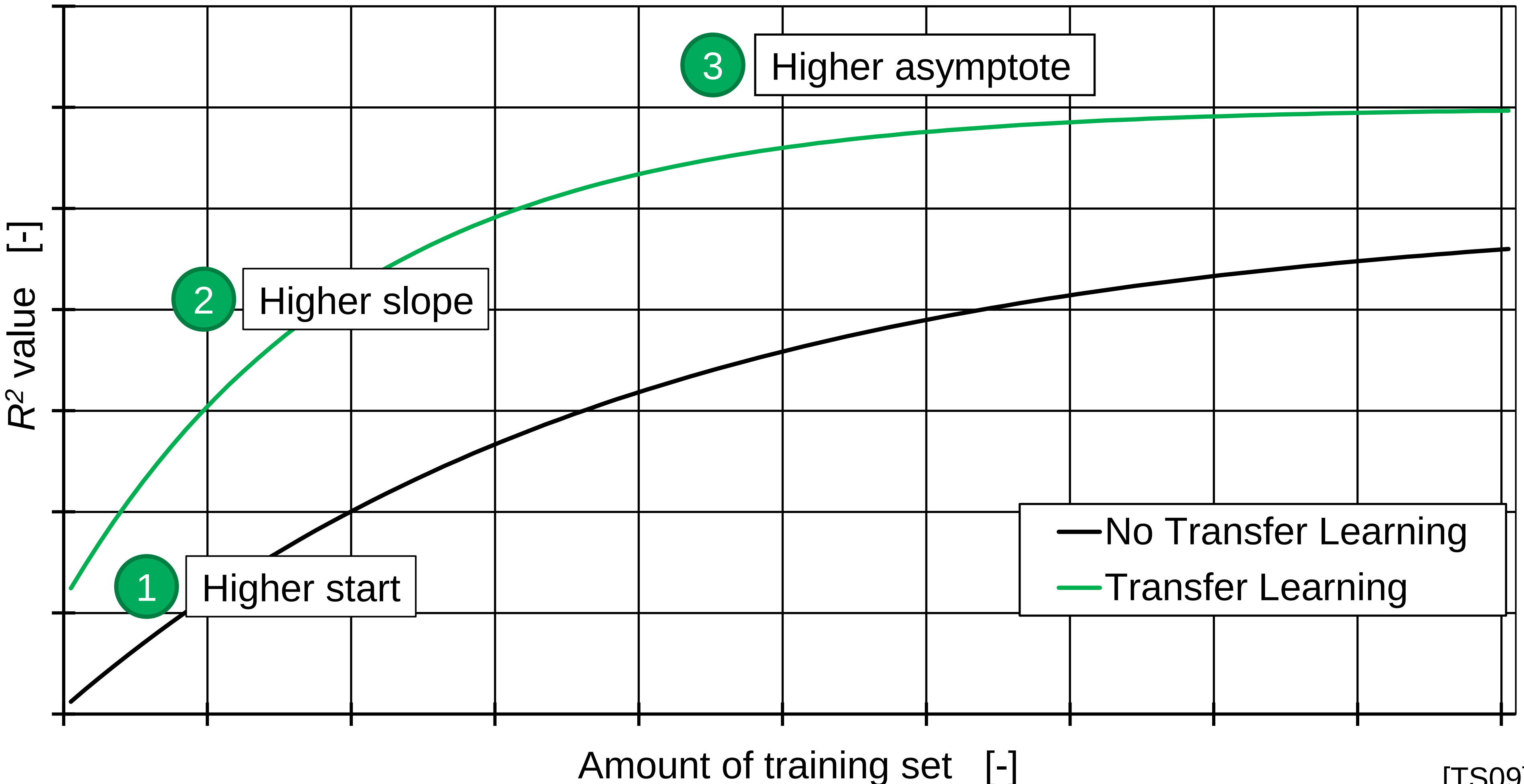


Possible advantages due to transfer learning



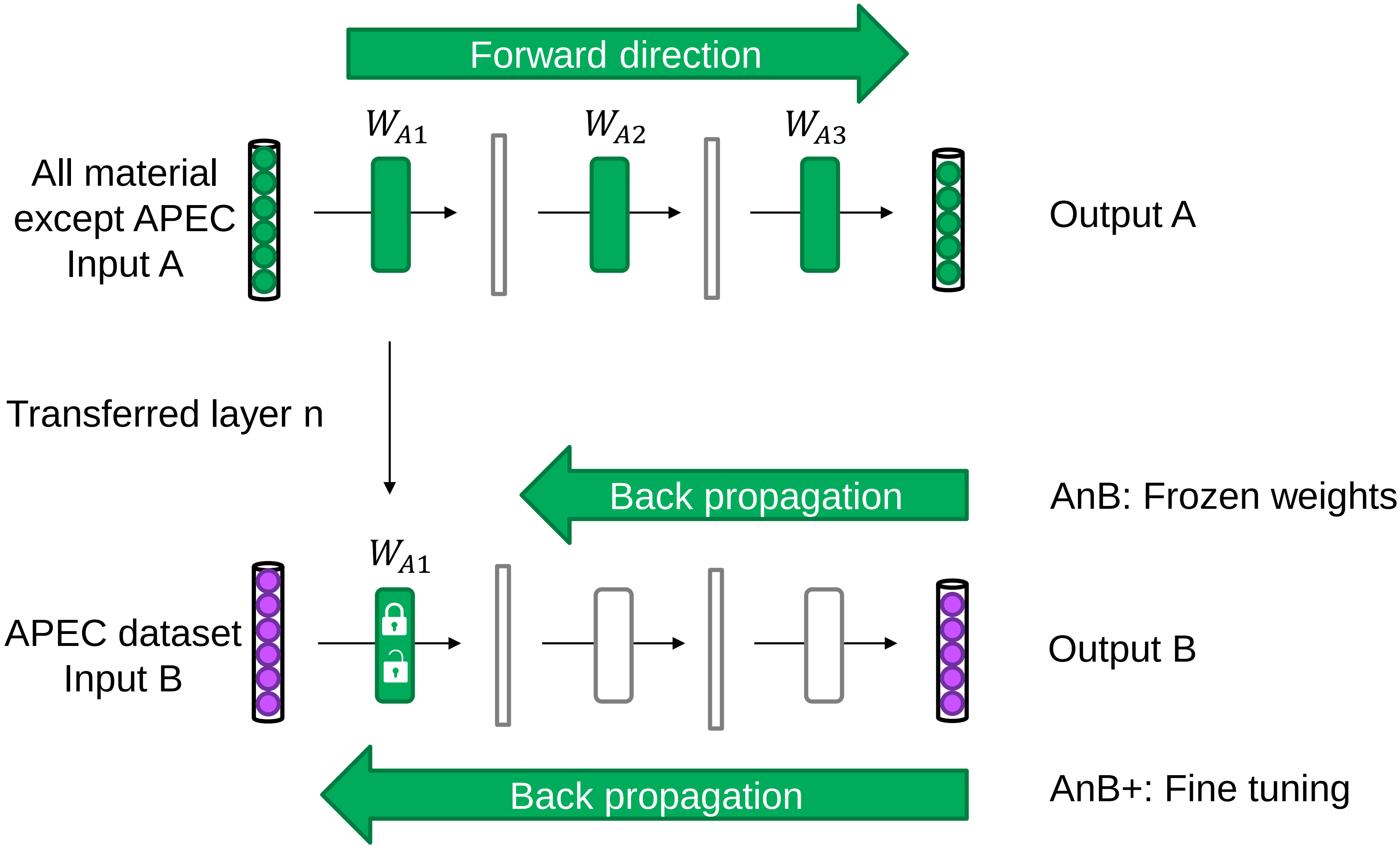
[TS09]

Possible advantages due to transfer learning



[TS09]

Difference of frozen weights and fine tuning



Generation of input features

Melt temperature
245 Step 1 270

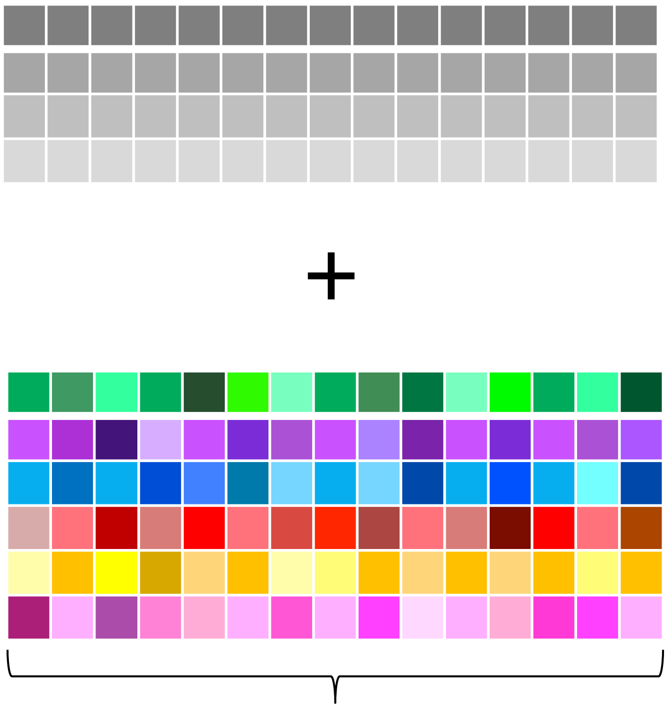
Cavity wall temperature
40 Step 1 100

Holding pressure time
0.2 Step 0.1 1.2

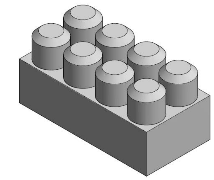
Cooling time
1.5 Step 0.1 2.5

Injection flow rate
30 Step 1 55

Holding pressure
400 Step 10 912



10000 samples with random machine settings

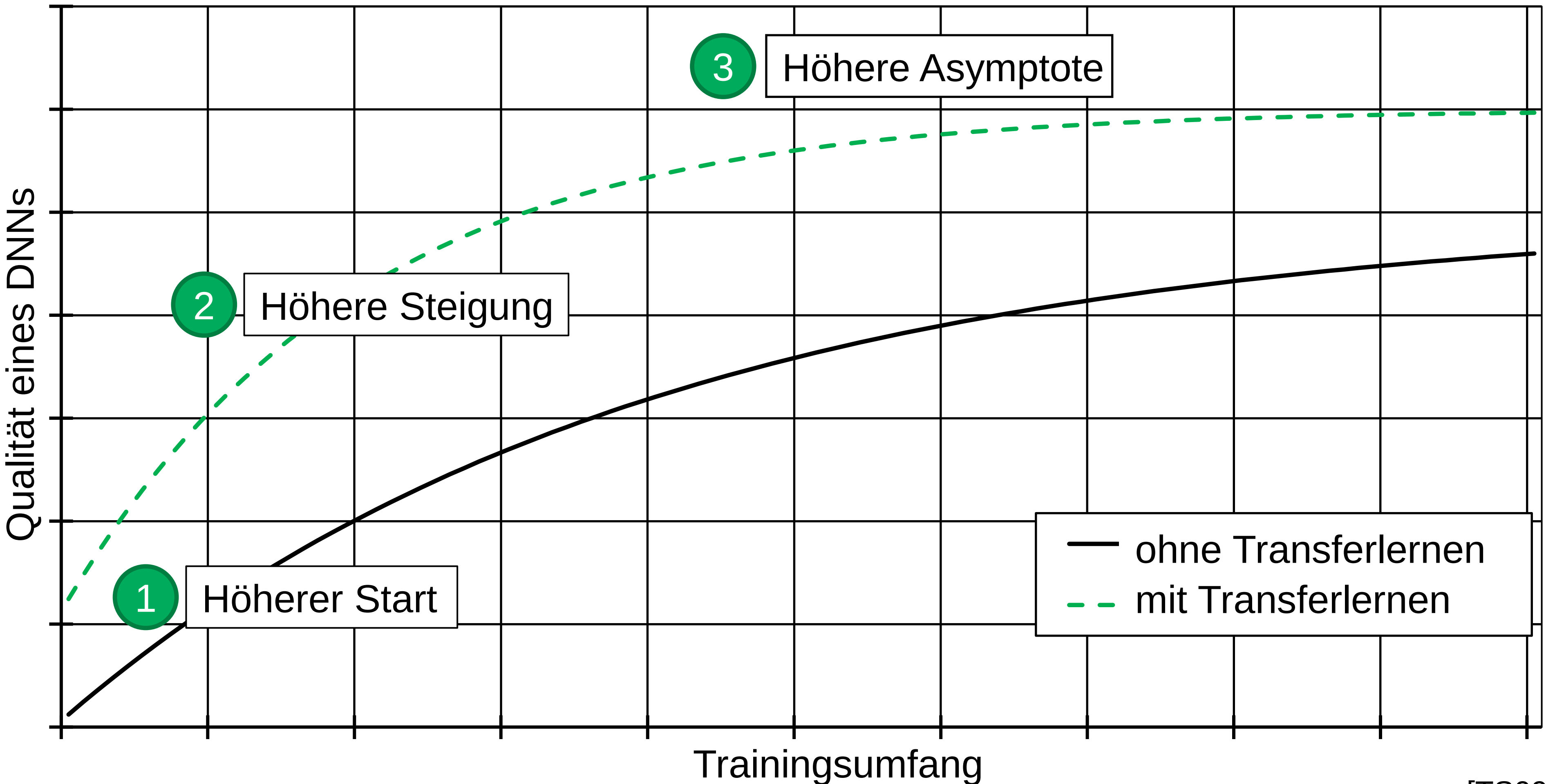


Material properties extracted from mould

Machine settings

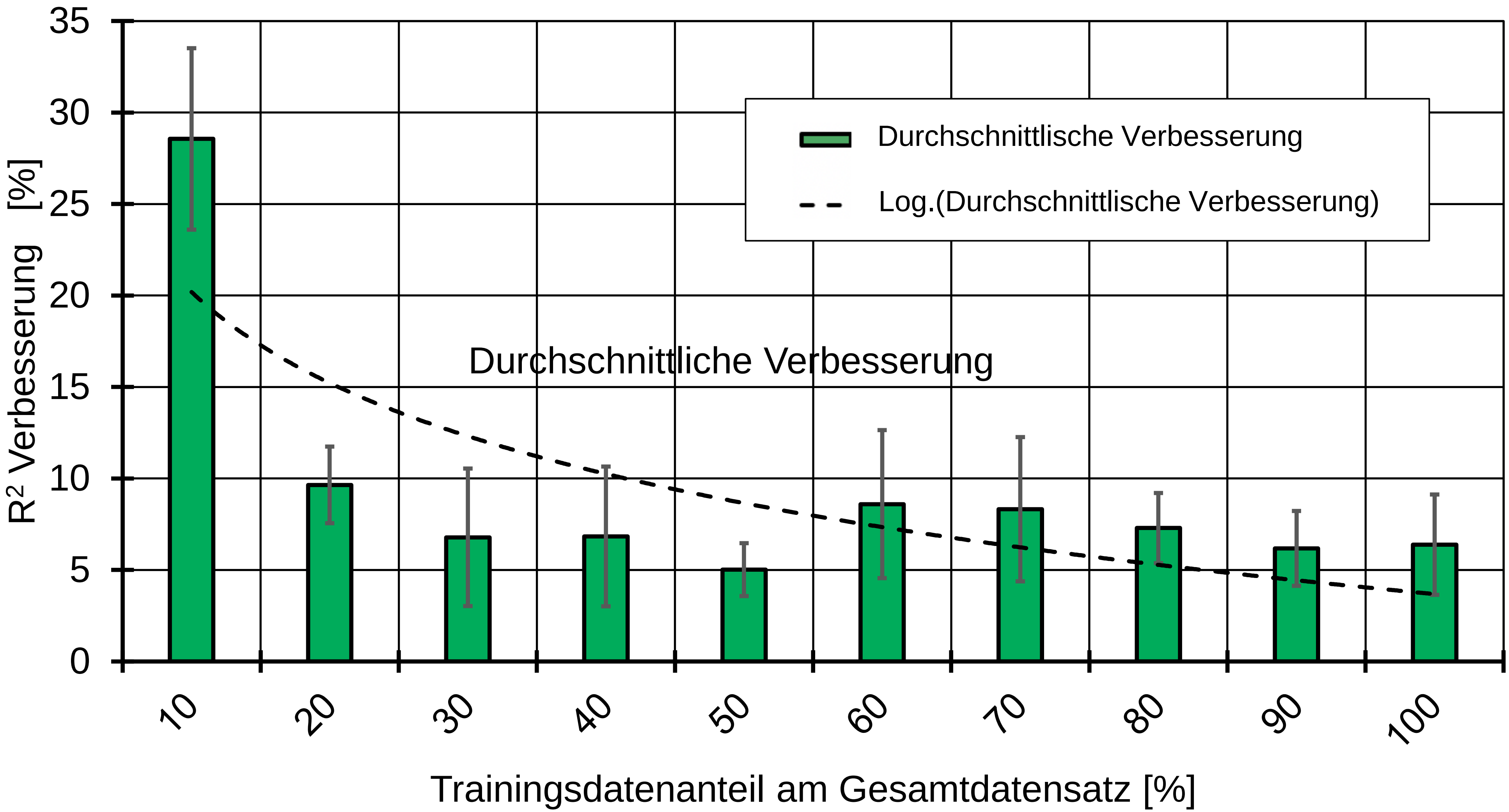
Thesis figures

Mögliche Vorteile durch Transferlernen

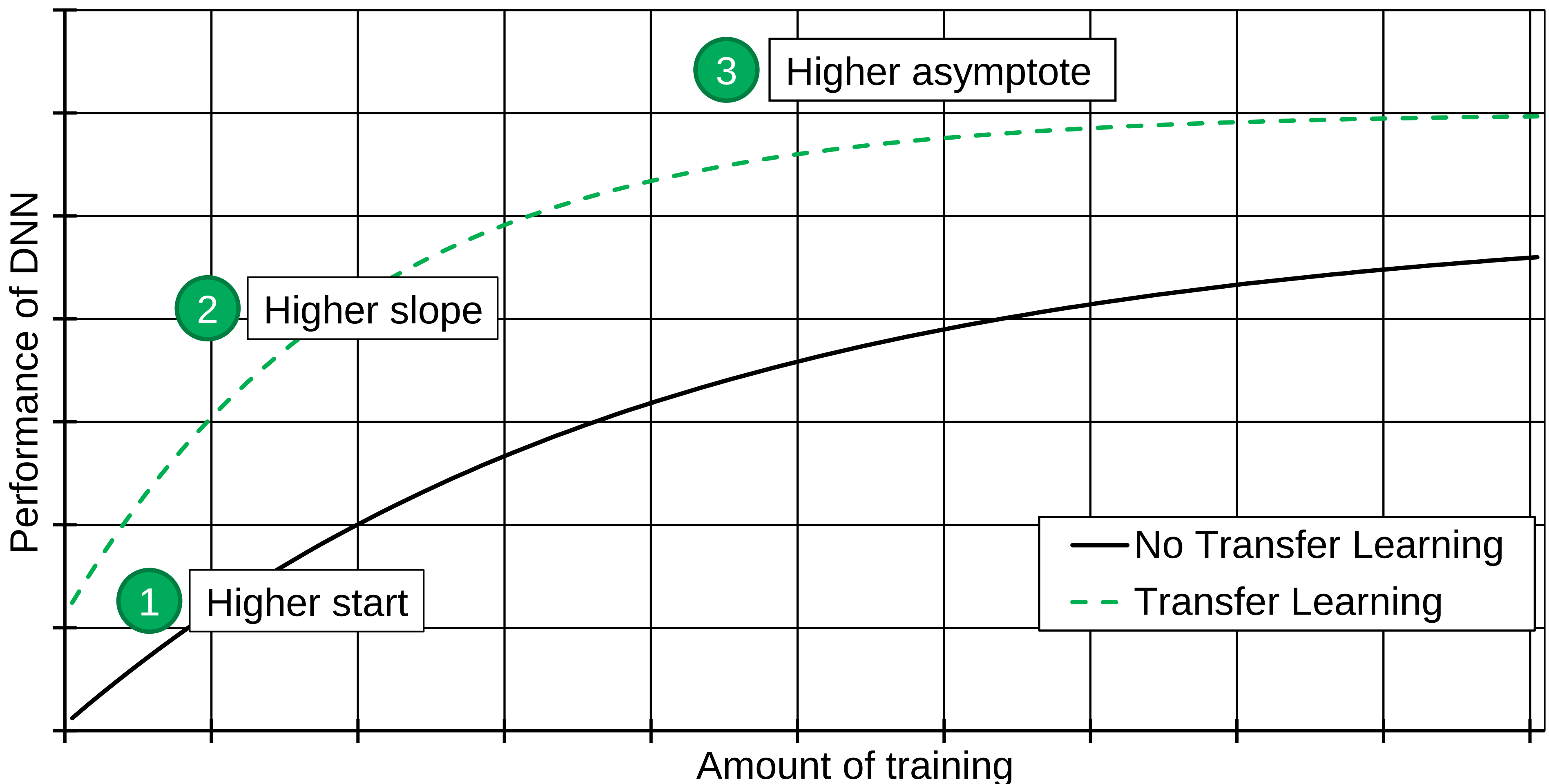


[TS09]

Verbesserung des R2-Werts durch Transferlernen bei Vorhandensein weniger Daten der APEC-Materialdomäne

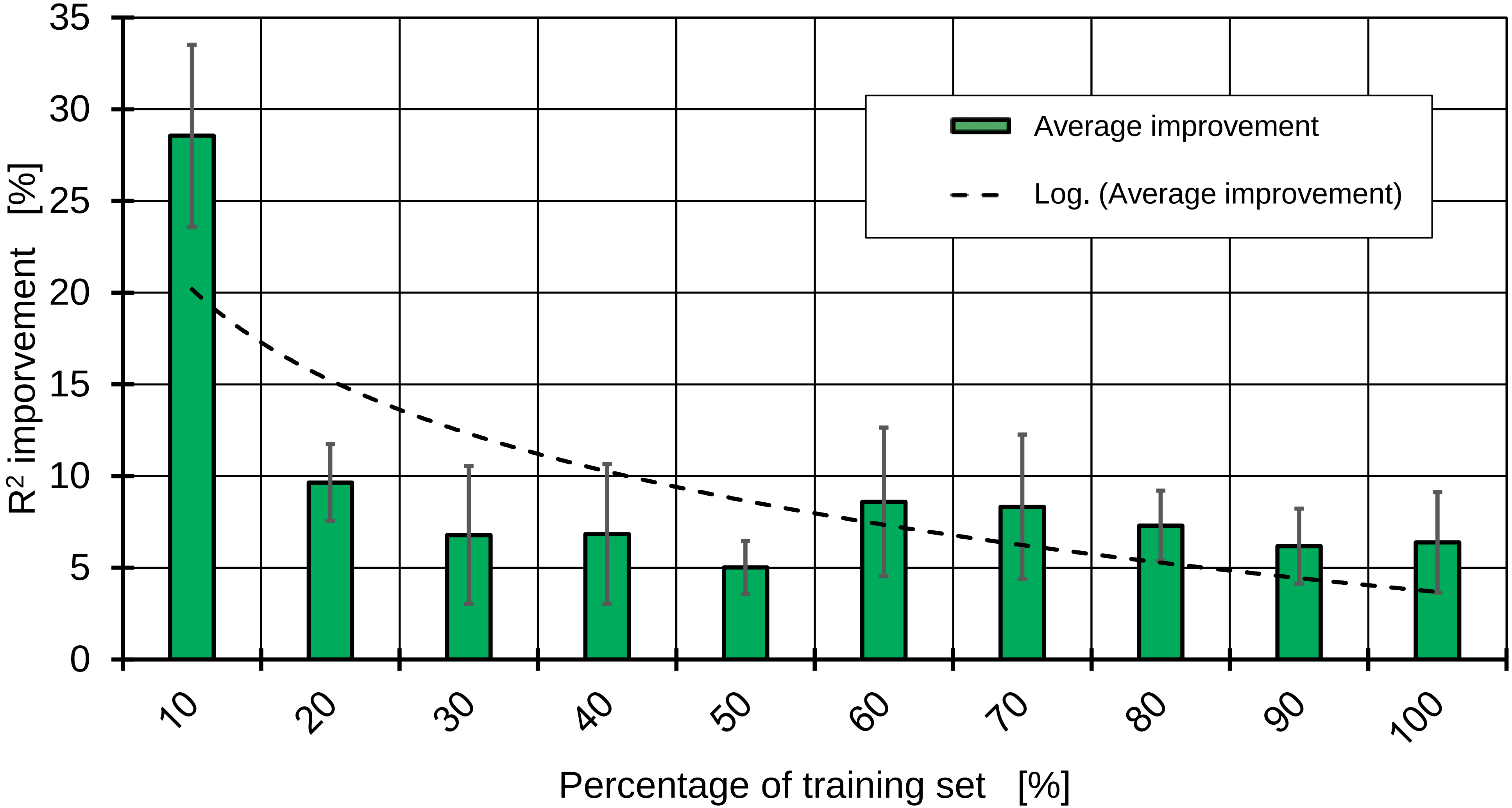


Possible advantages due to transfer learning

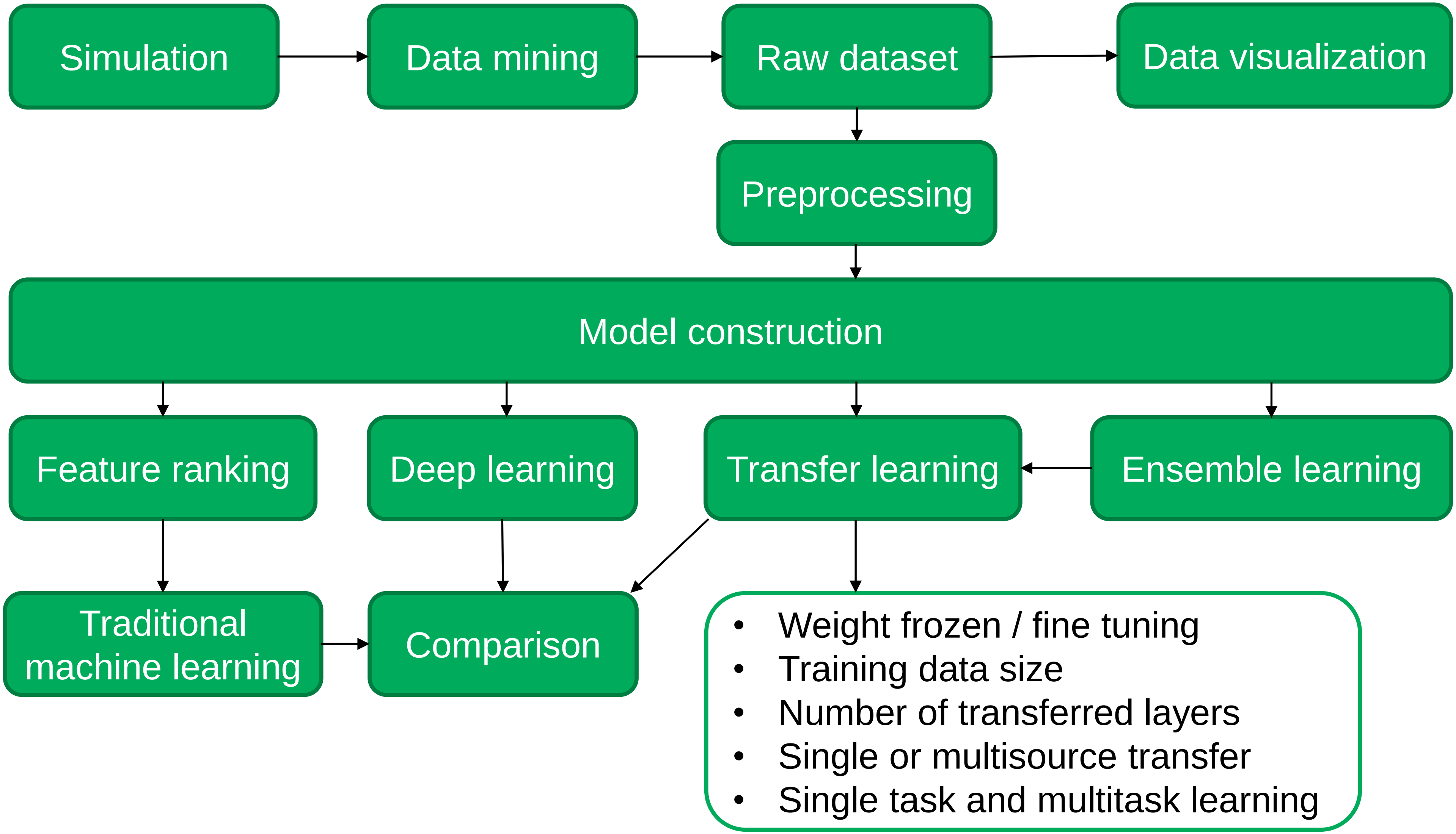


[TS09]

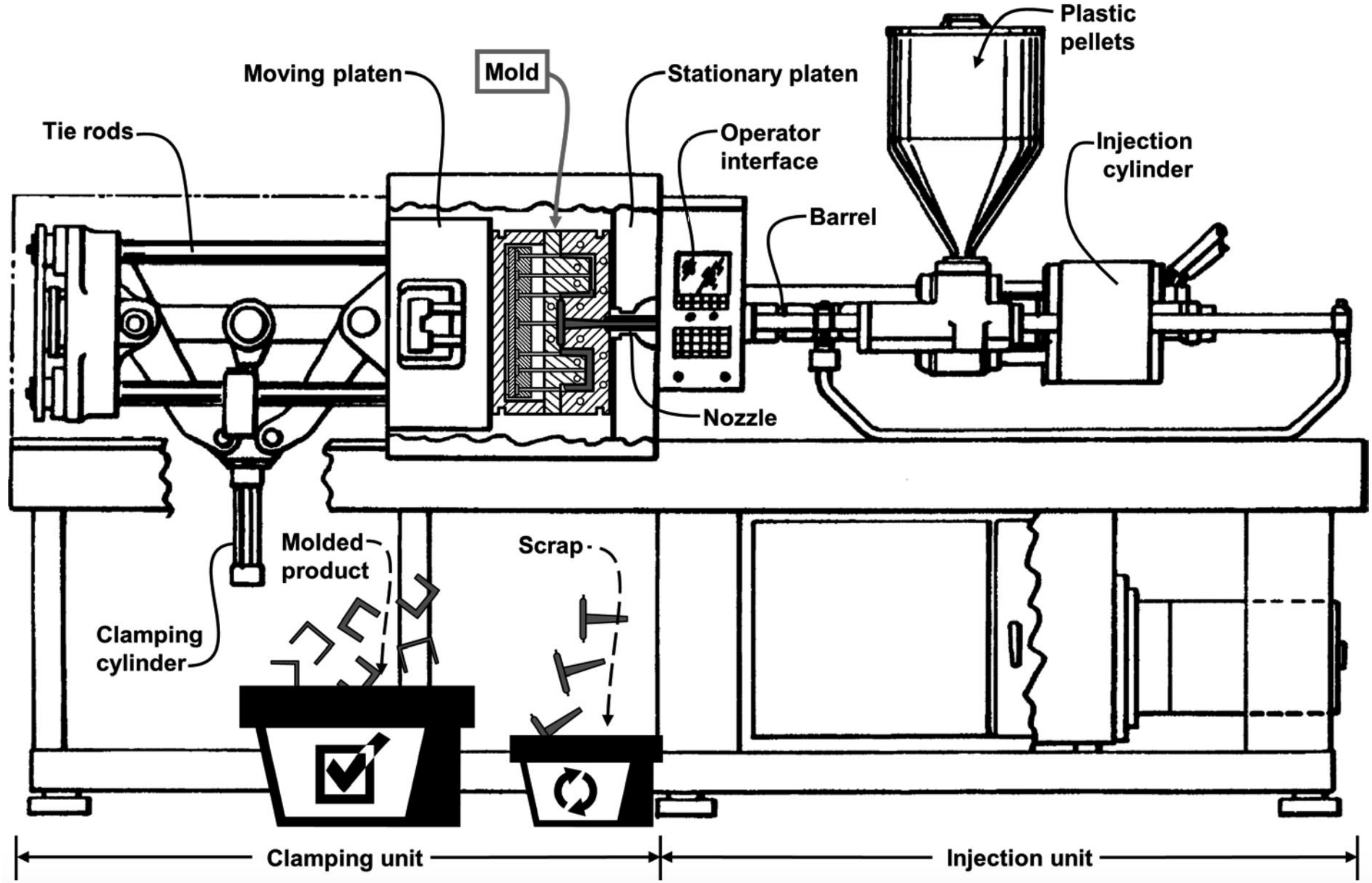
Improvement of the R^2 value by transfer learning in presence of few data from the APEC material domain



Research methodology approach

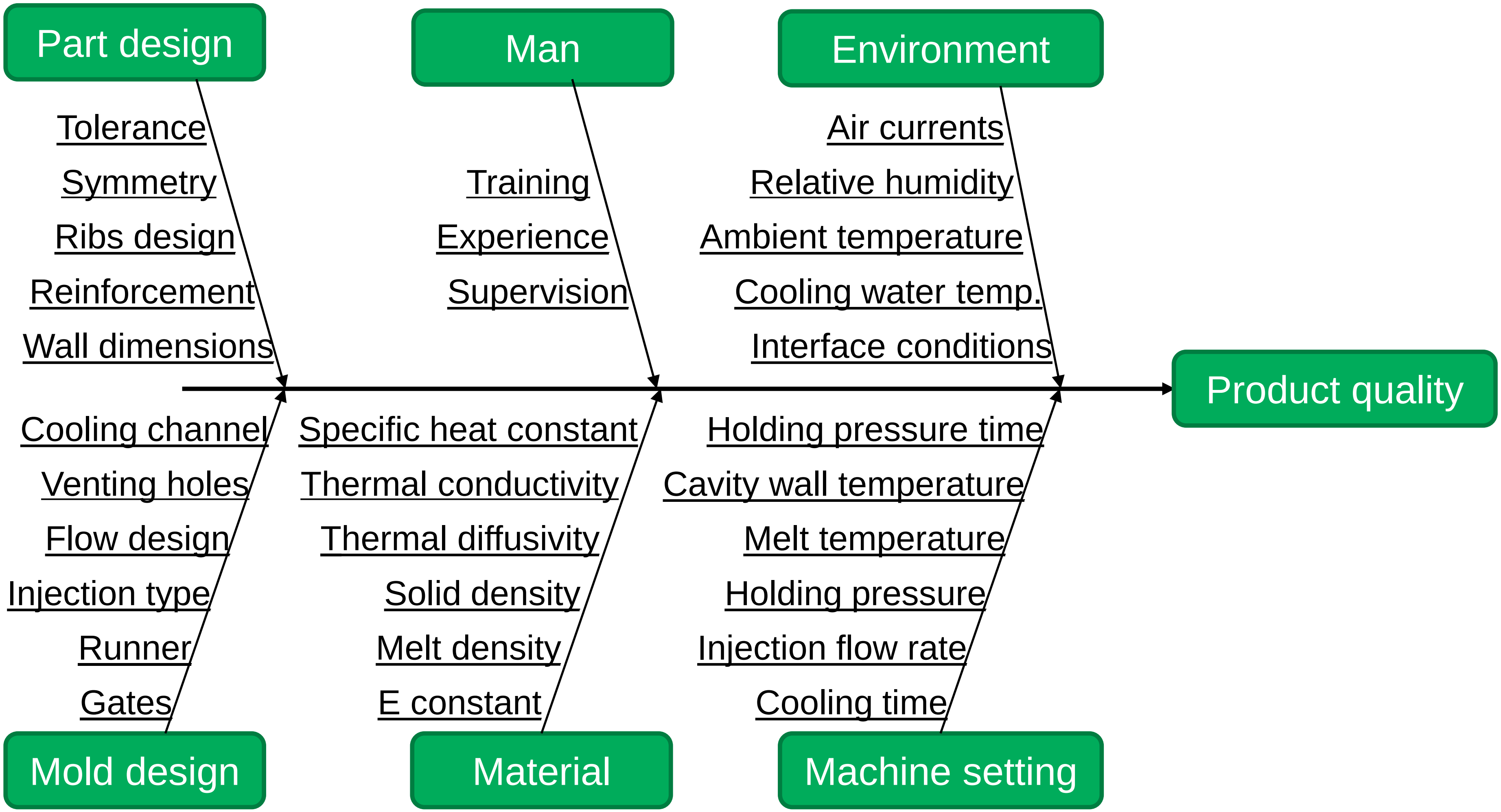


Depiction of an injection moulding machine



[Kra05]

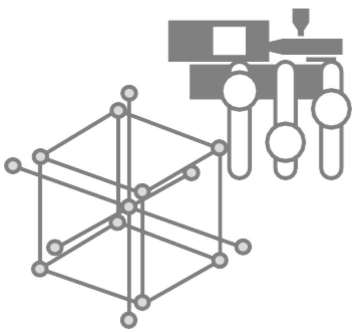
Influence factors of product quality in injection moulding



[STT+08]

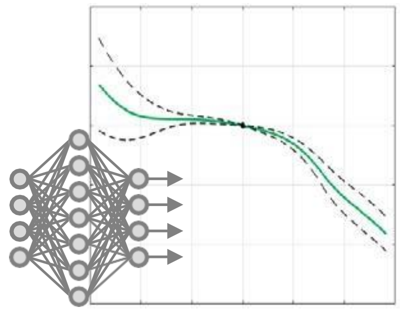
Process setup by means of machine learning

Design of experiments

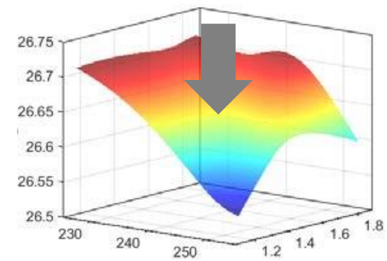


Injection moulding simulation

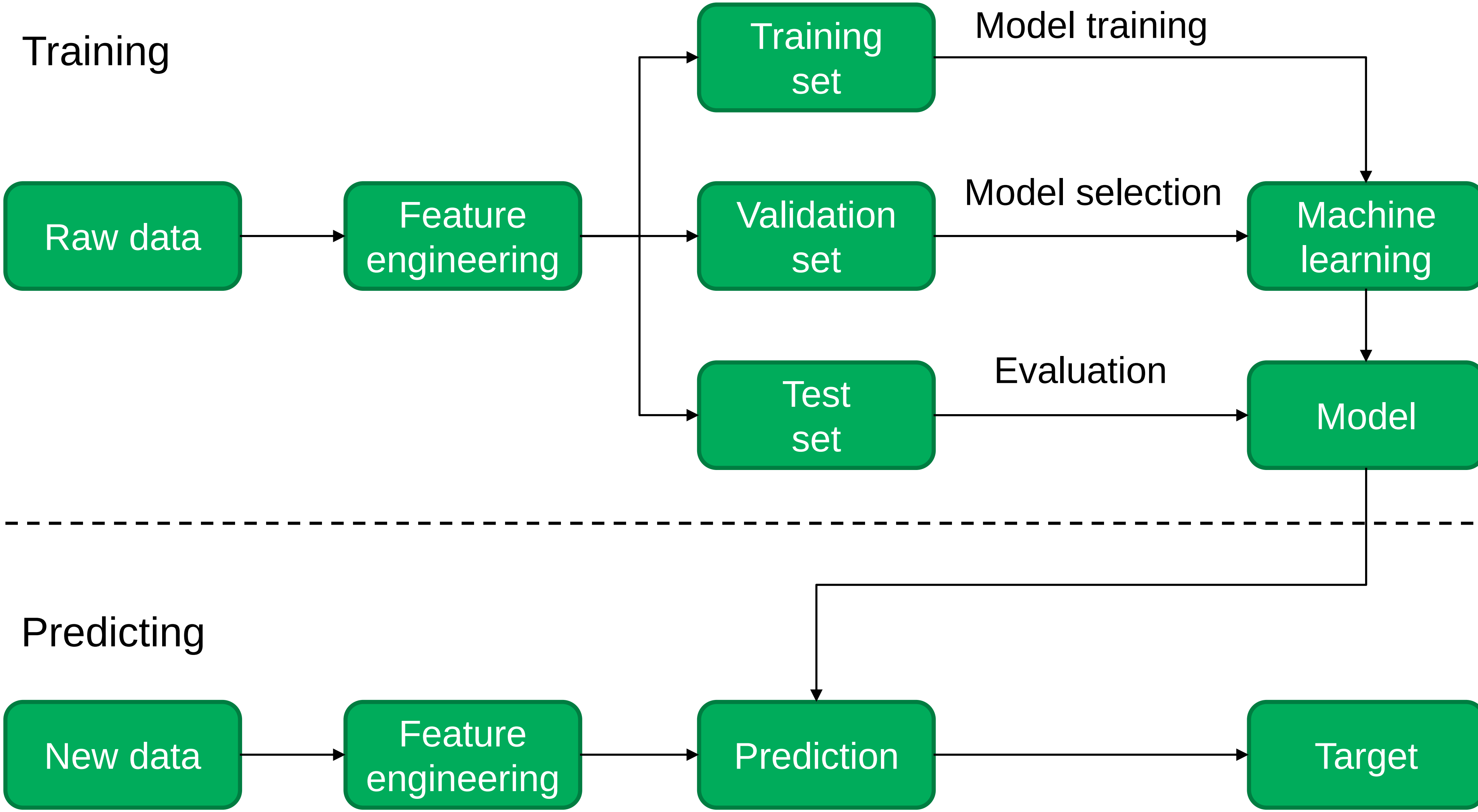
Model construction



Optimisation

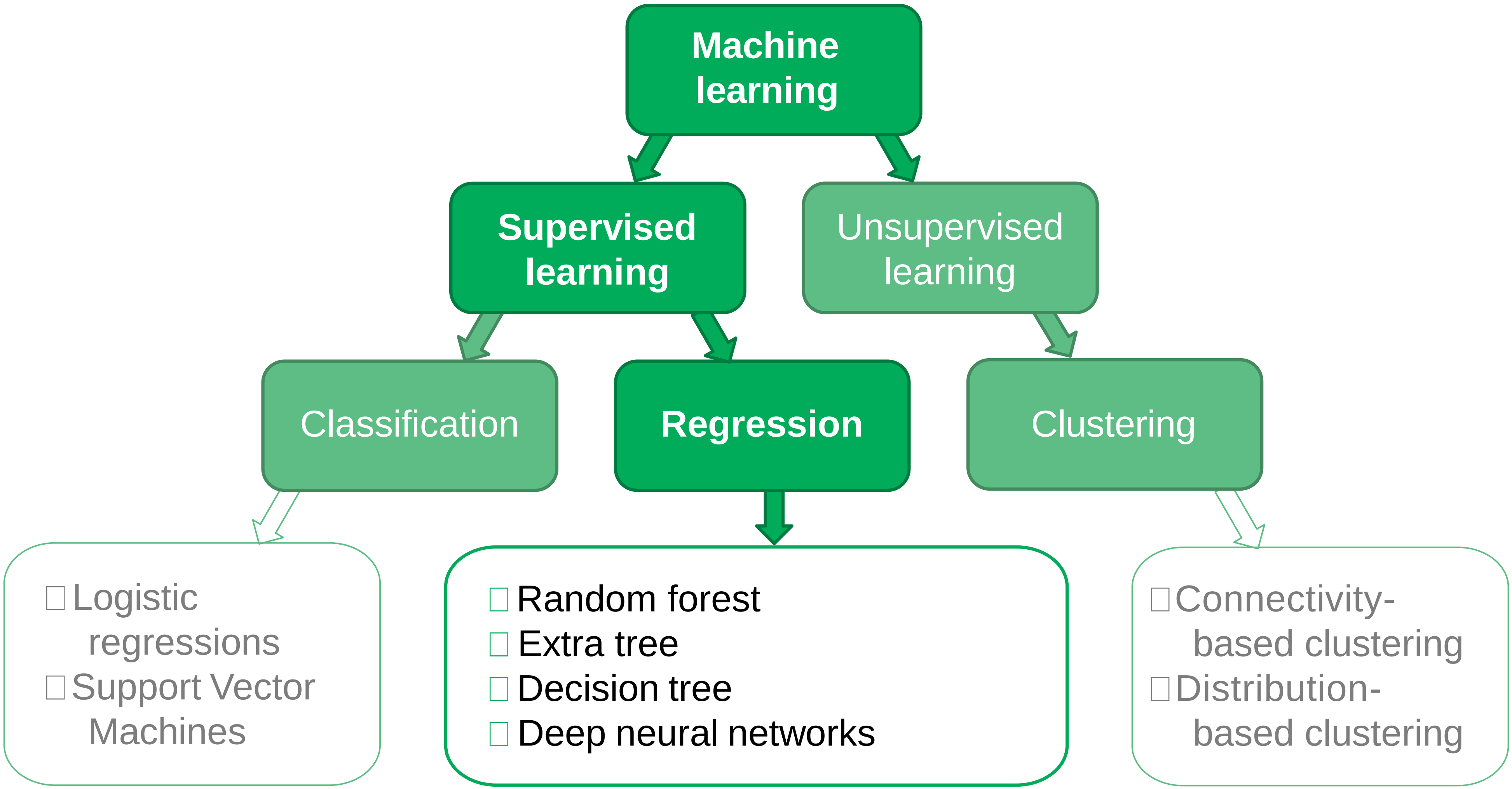


A practical view of a machine learning system



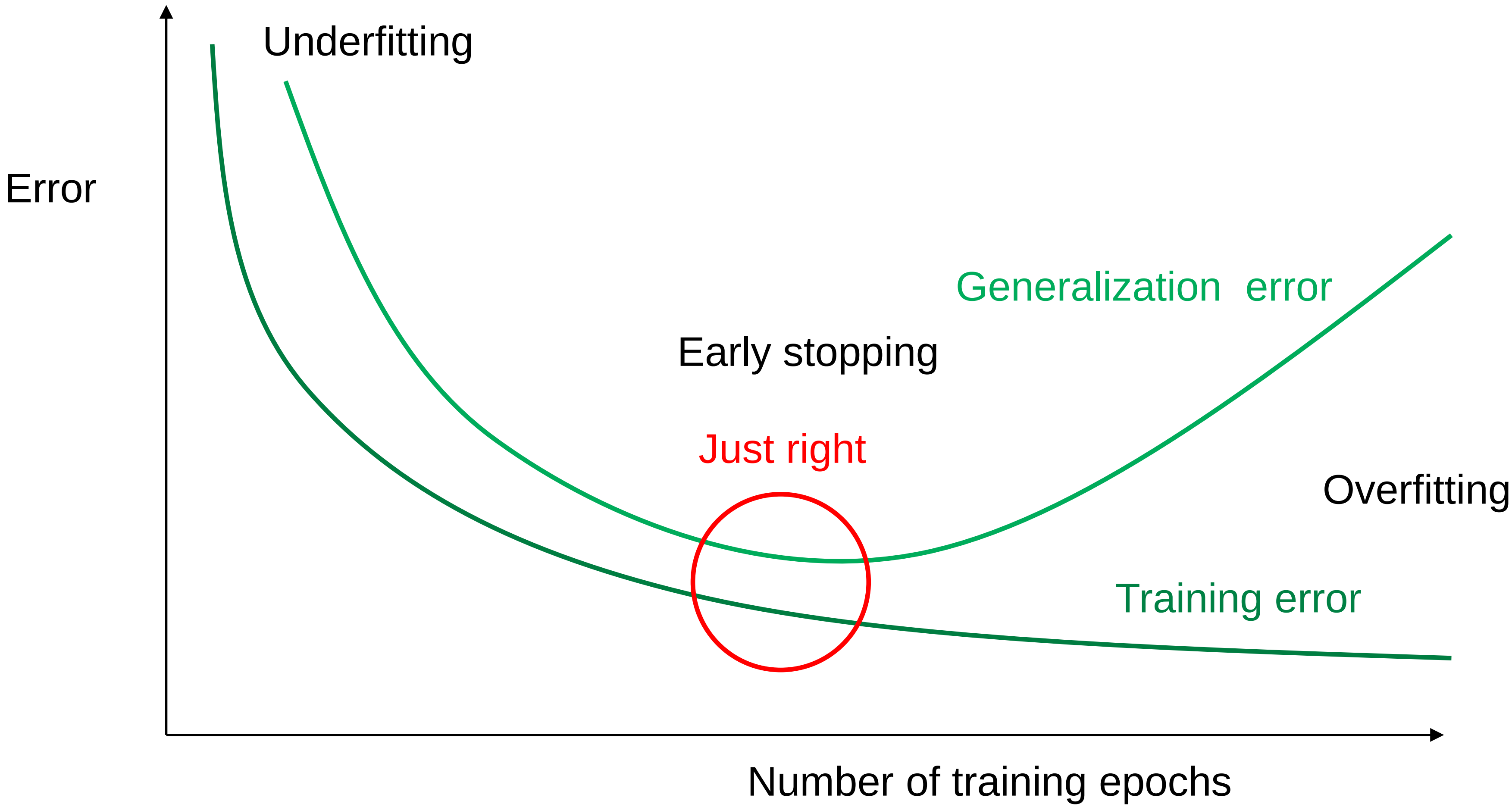
[Osm19]

Methods of machine learning



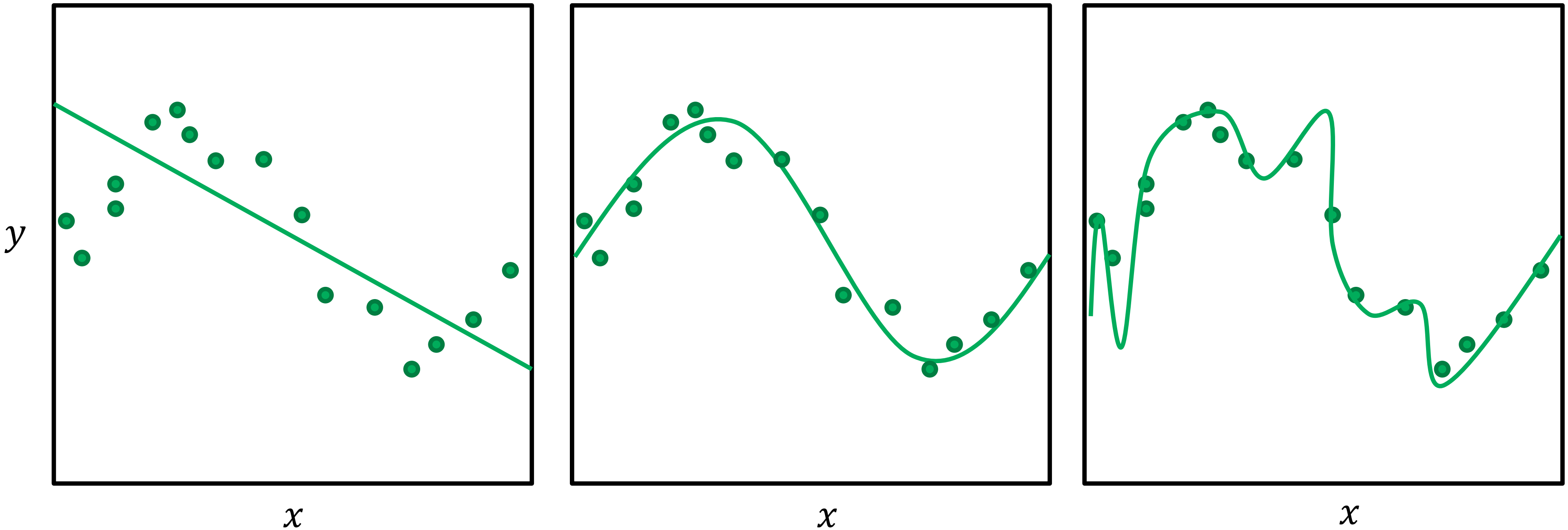
[Mit97]

Model performance influenced by number of training epohcs



[GBC16]

Comparison of underfitting, appropriate fitting and overfitting



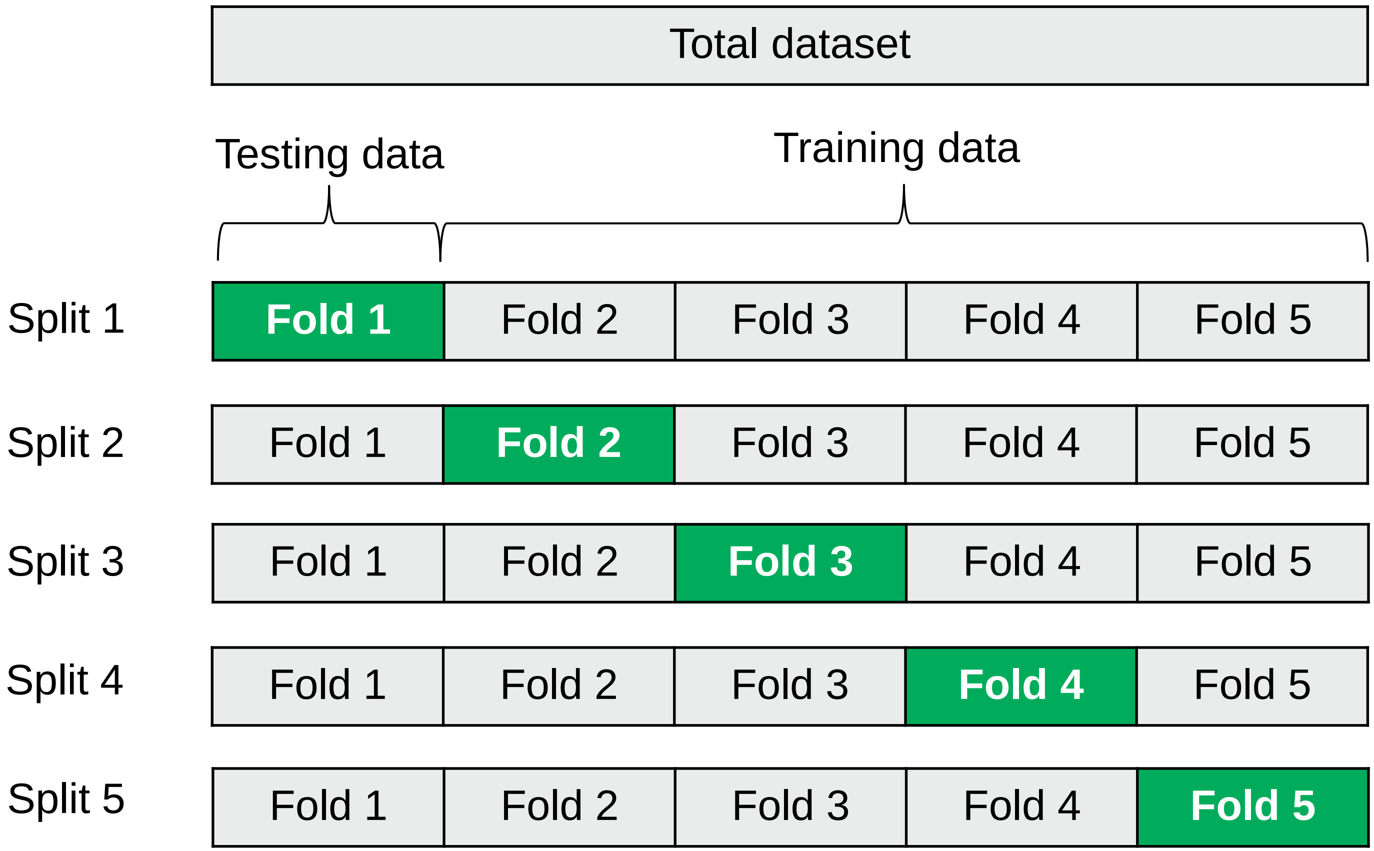
Underfitting
(Too simple to explain the variance)

Appropriate fitting
(Good Generalization)

Overfitting
(Too good to be true)

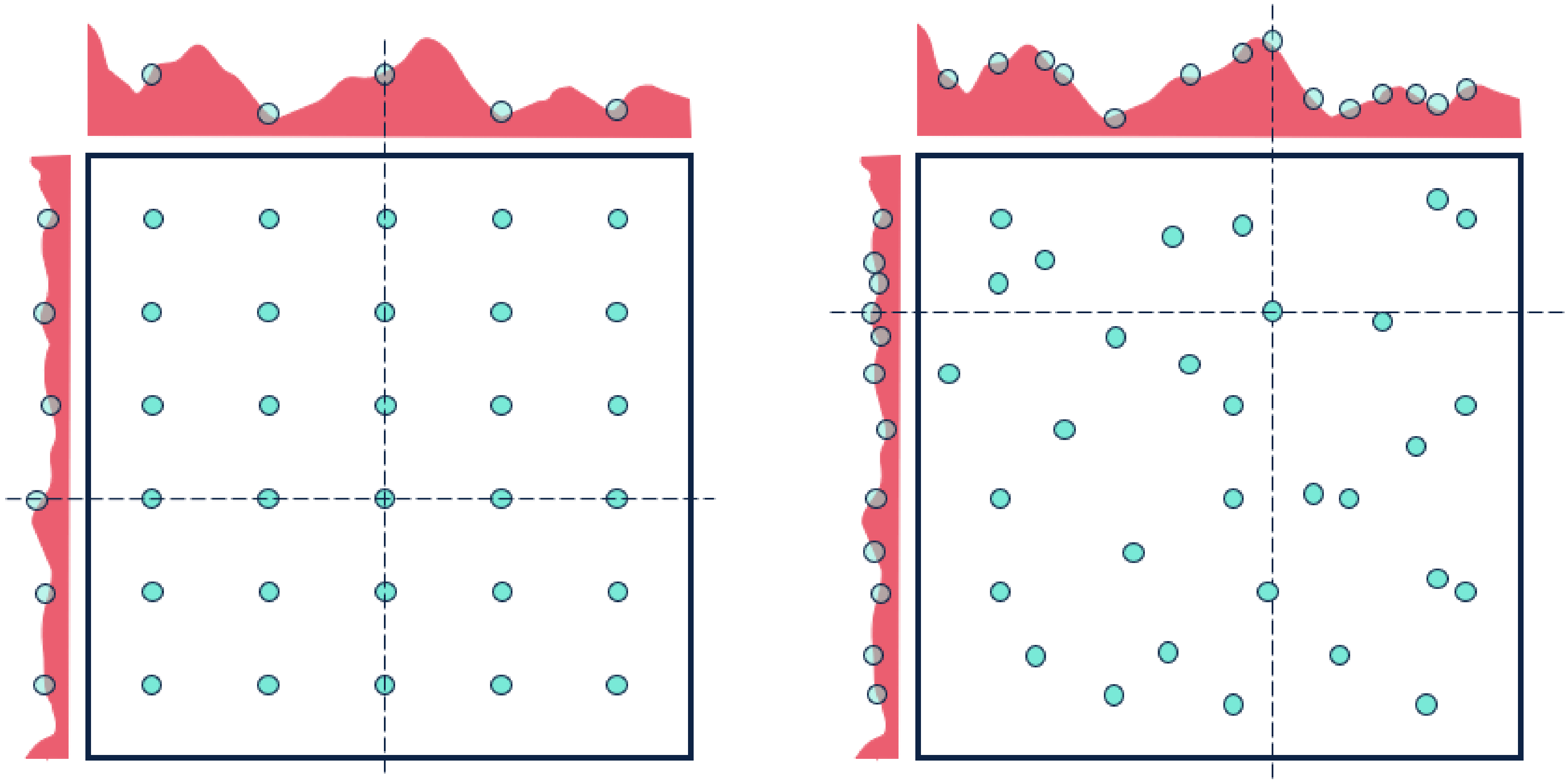
[FW95]

Cross validation



[JH15]

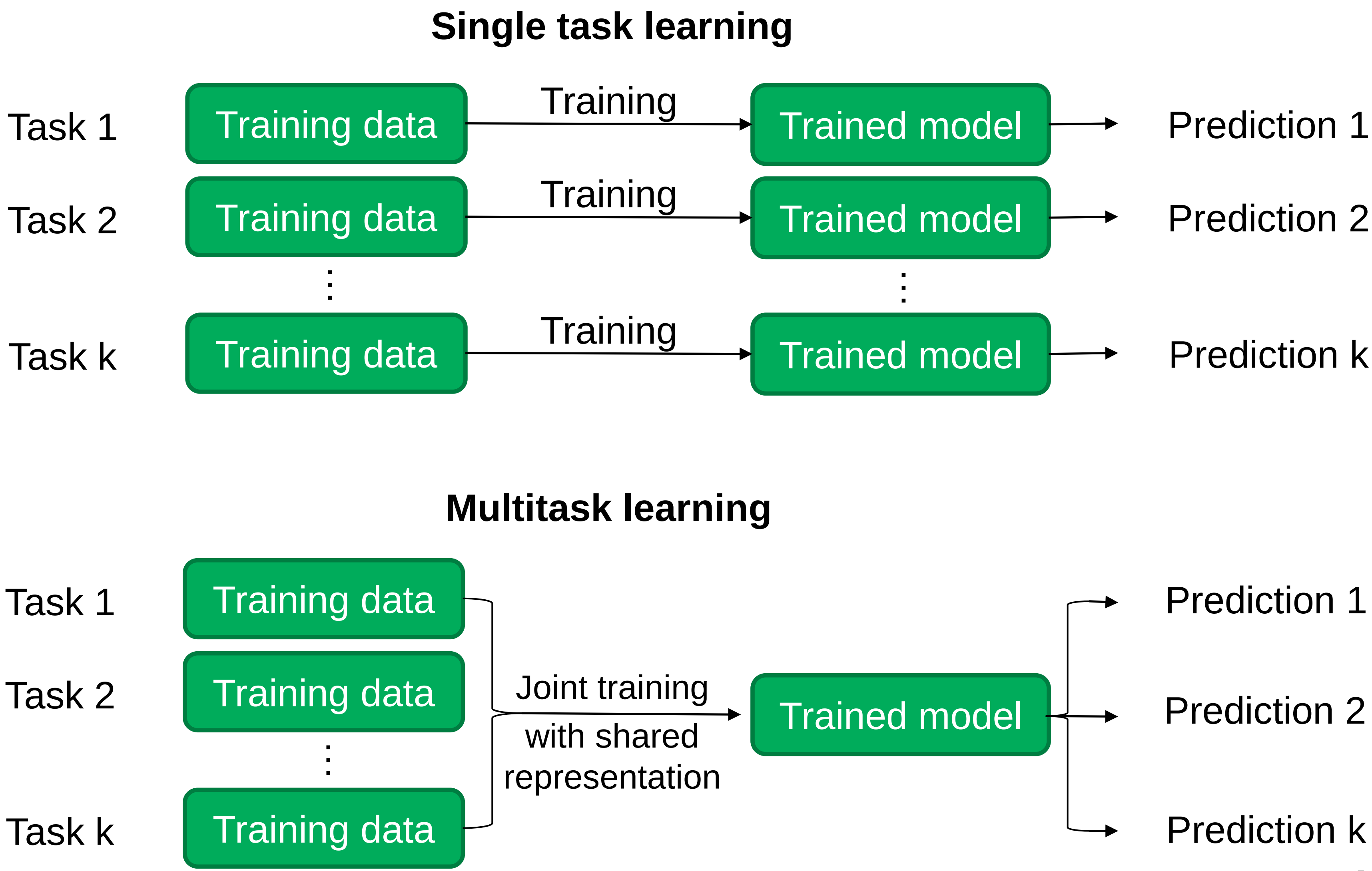
Hyperparameter tuning



Grid search | Random search

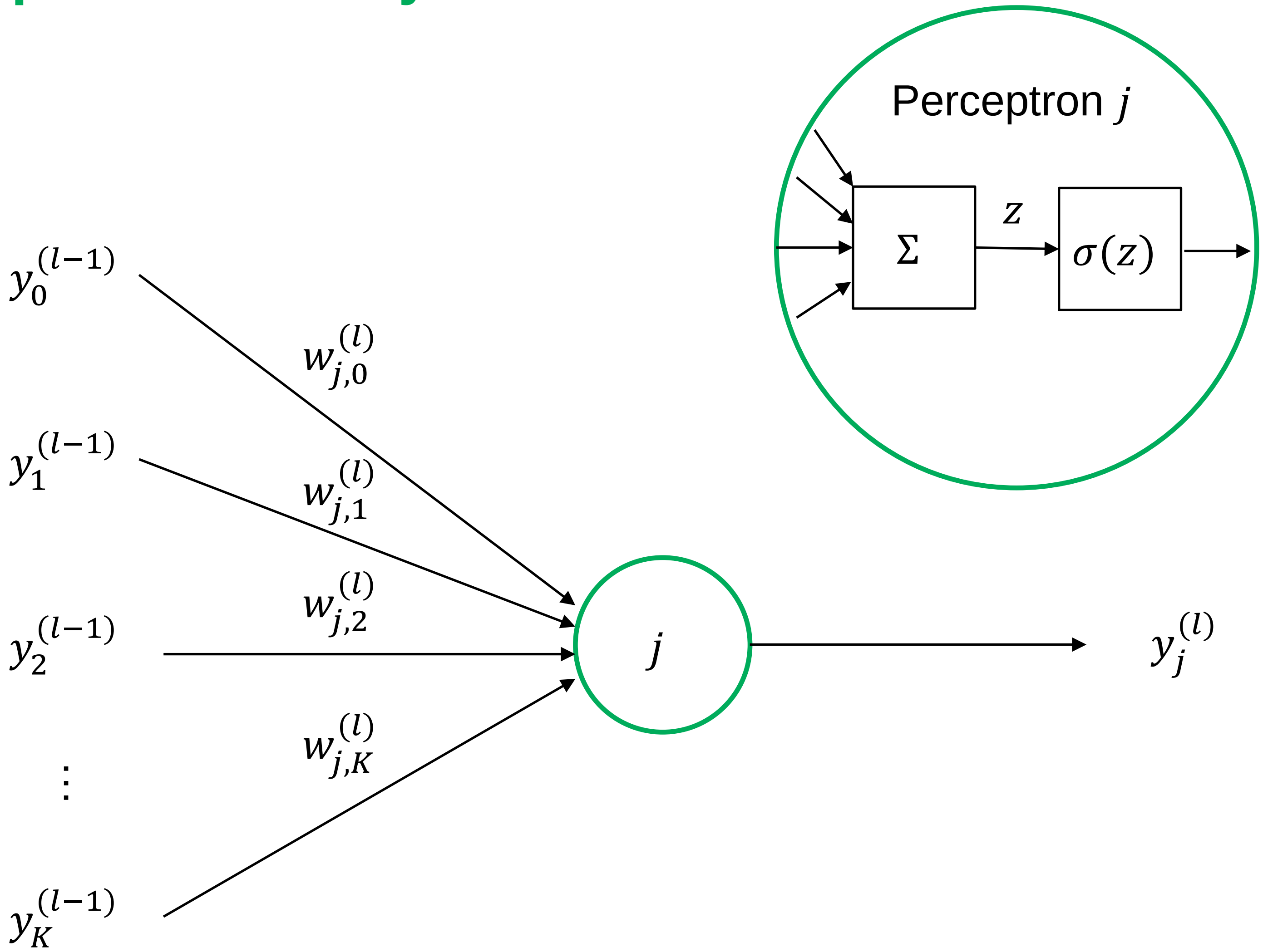
[BB12]

Different concepts of single task learning and multitask learning



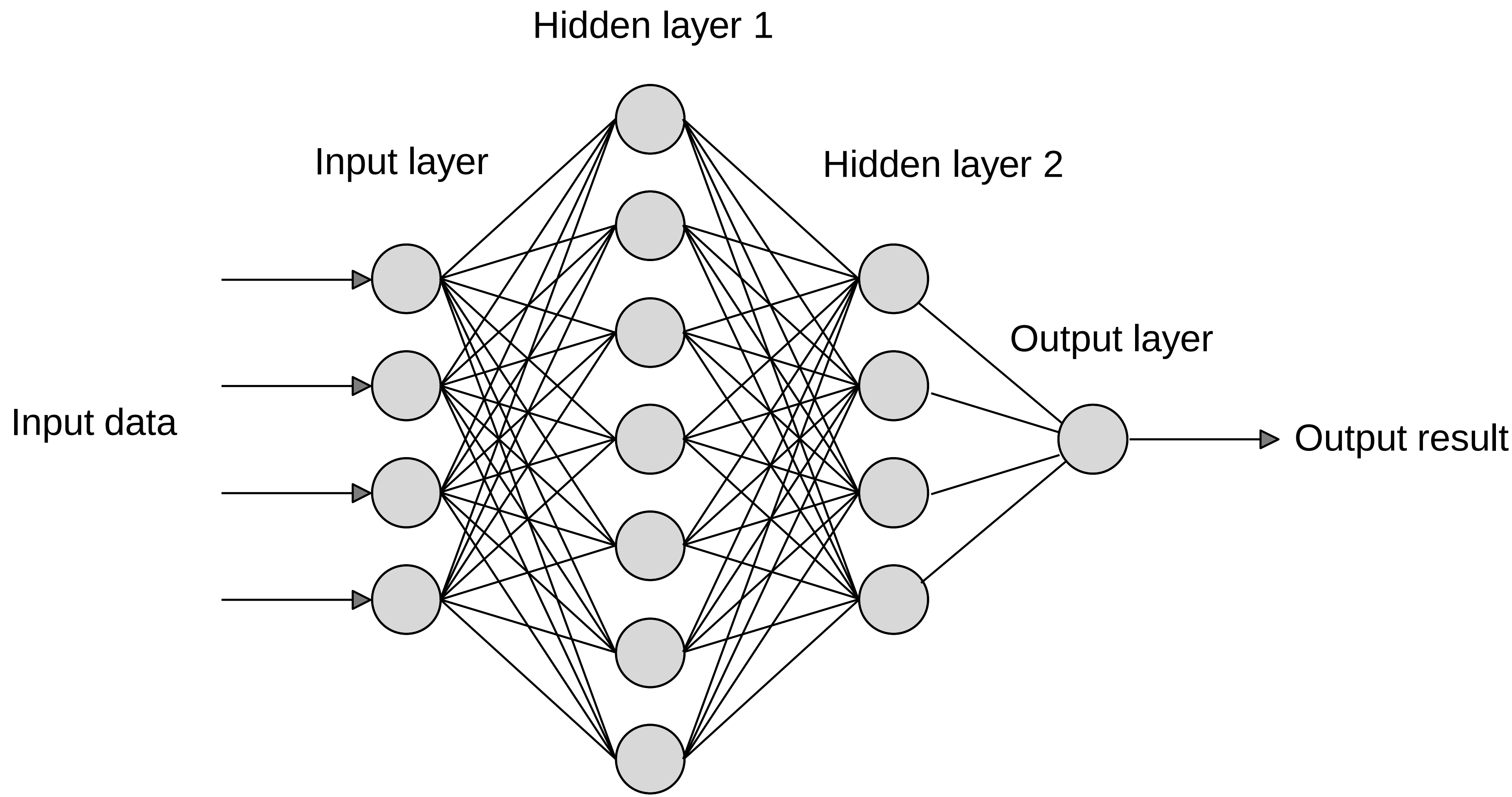
[Car93]

One perceptron of the layer l



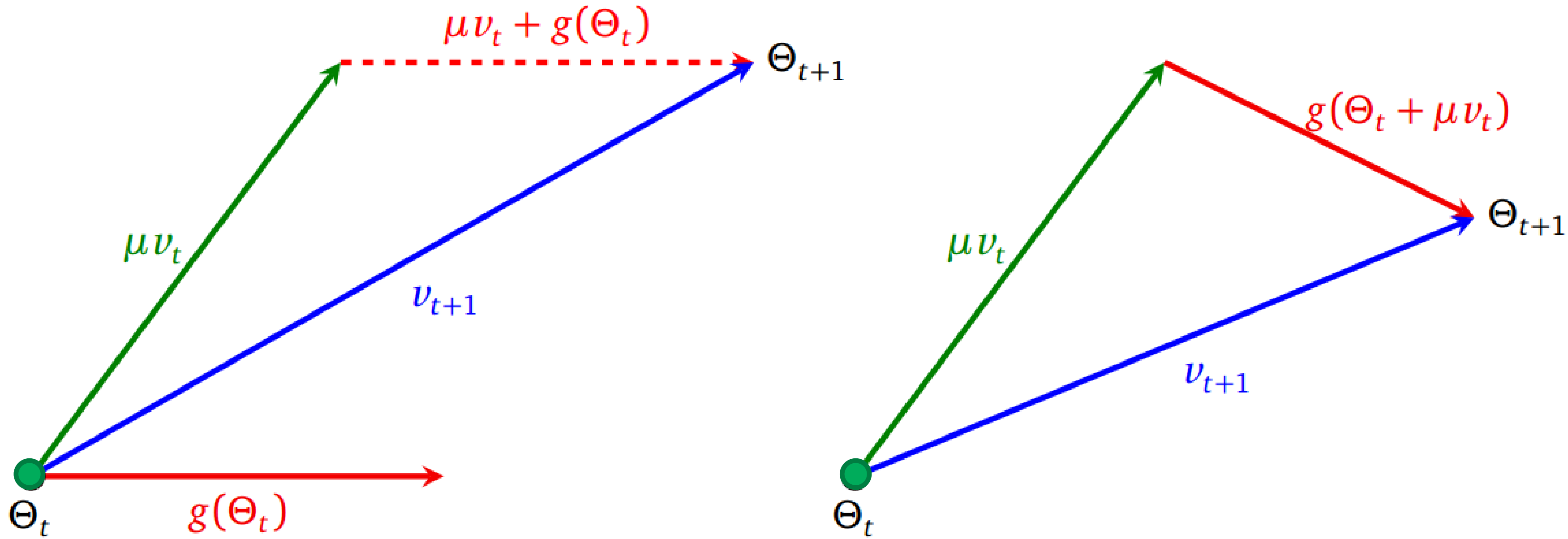
[JZL18]

Stucture of deep neural network (DNN)



[Saz06]

Difference between momentum update and Nesterov momentum update

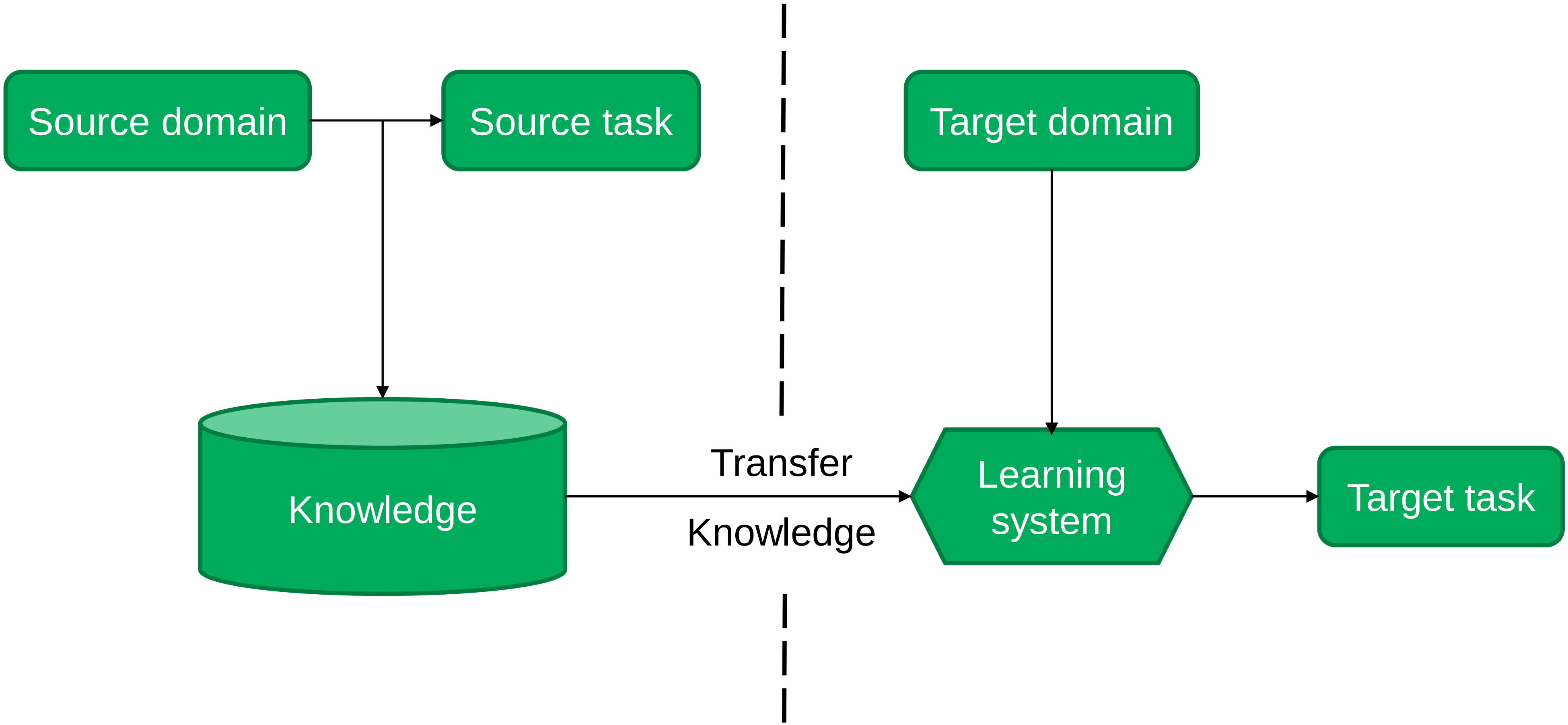


Momentum update

Nesterov momentum update

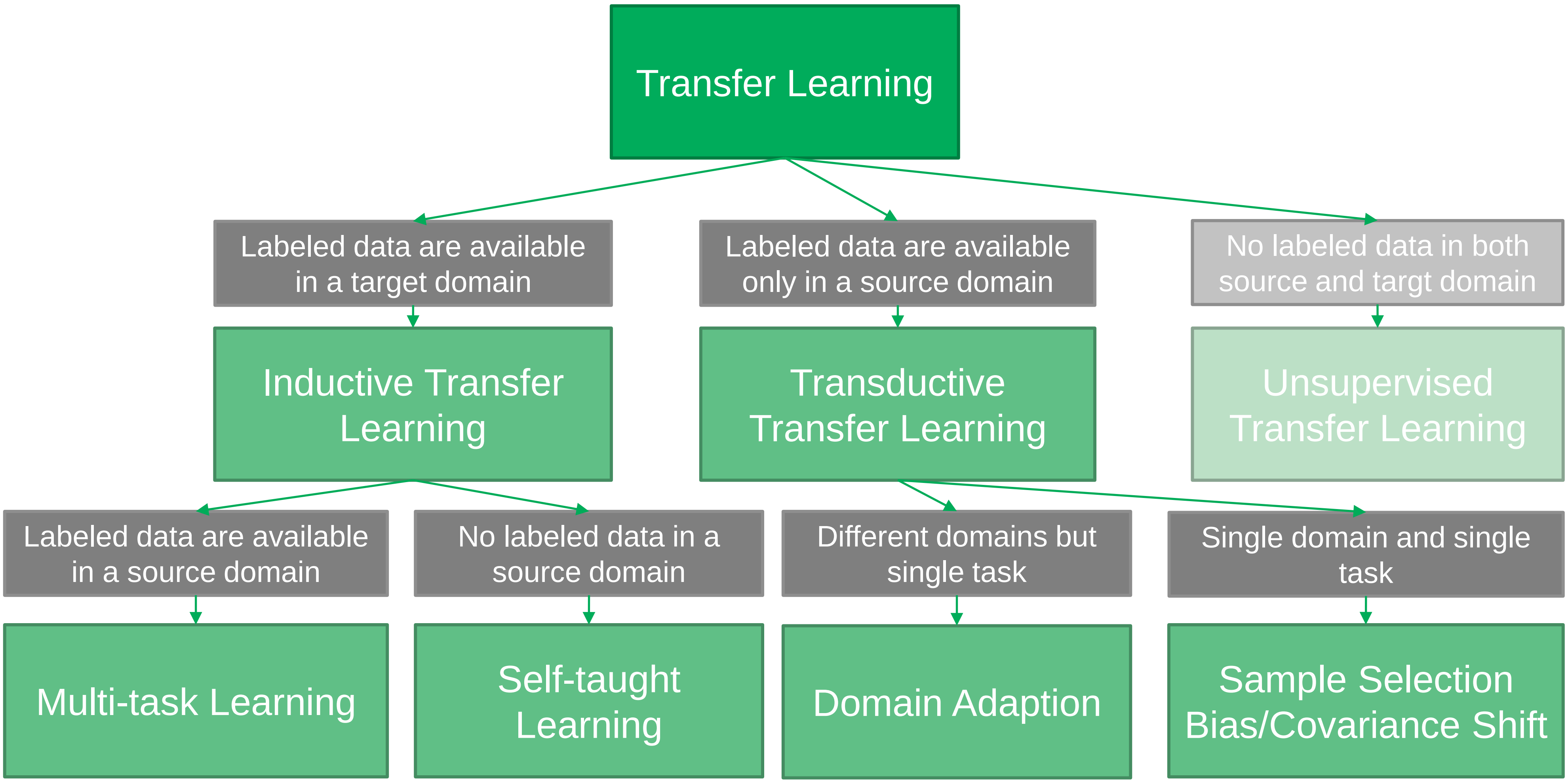
[SMD13]

Fundamental approach of transfer learning



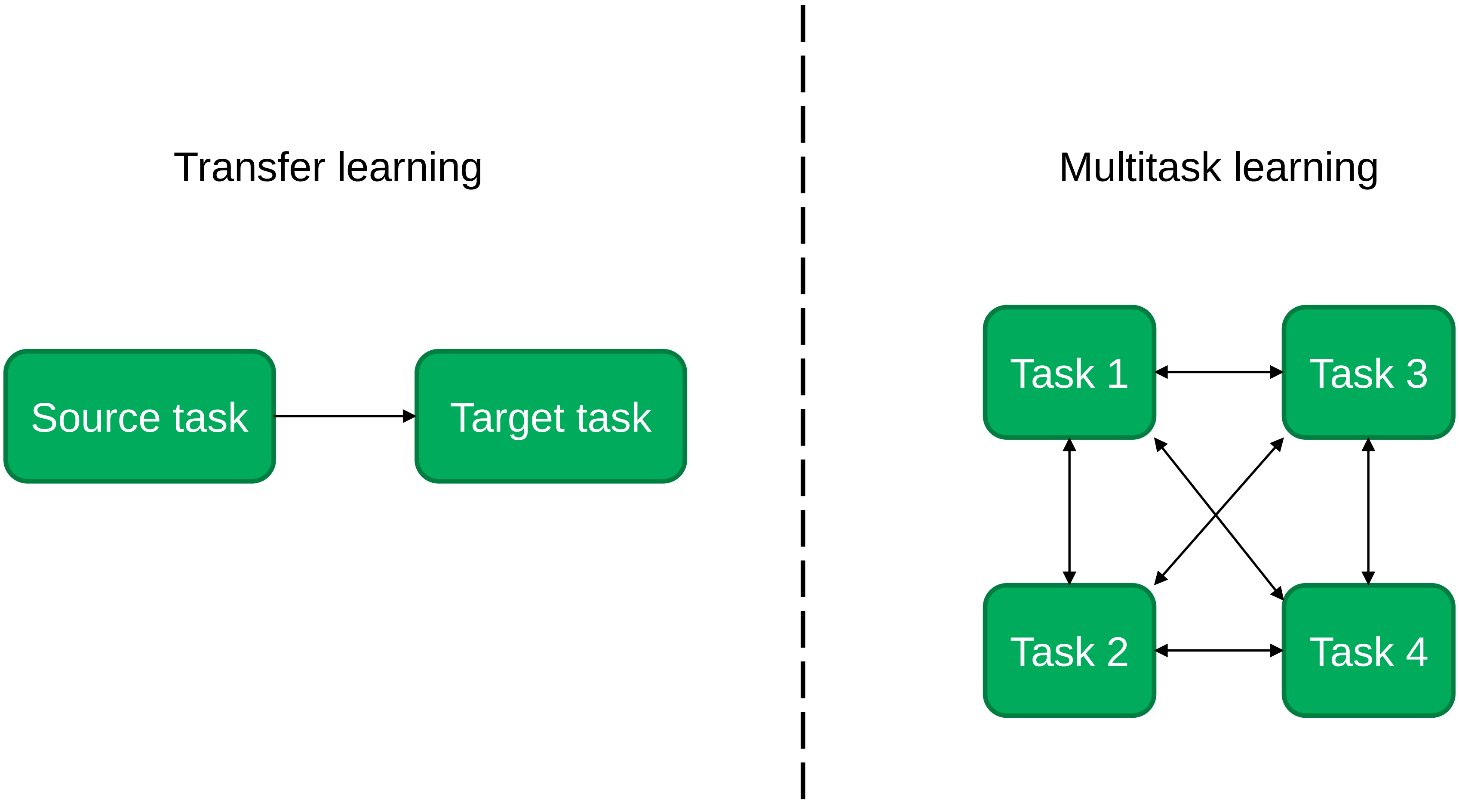
[OBL14]

Categorization of transfer learning approaches



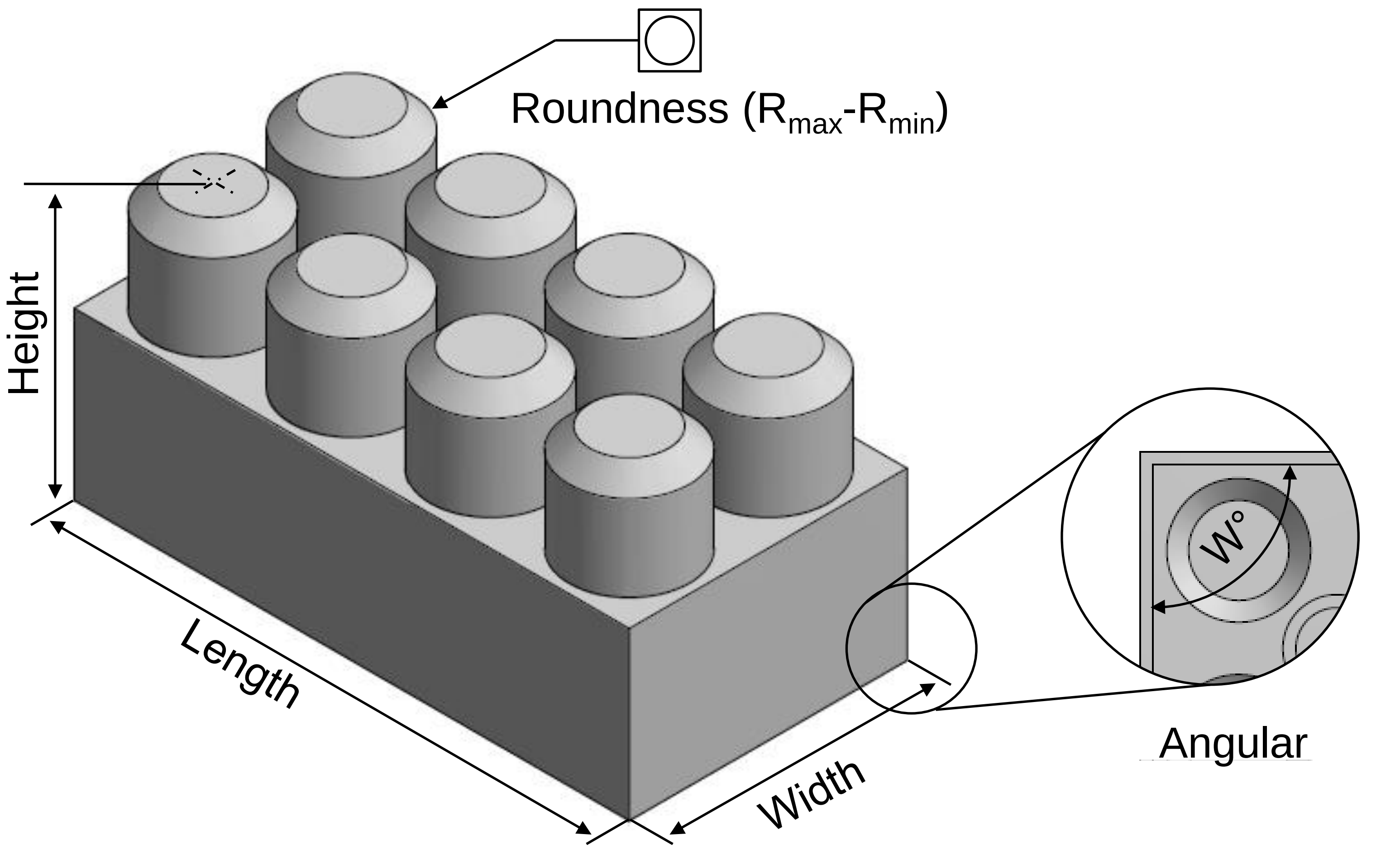
[ZLO17]

Distinction between transfer learning and multi-task learning

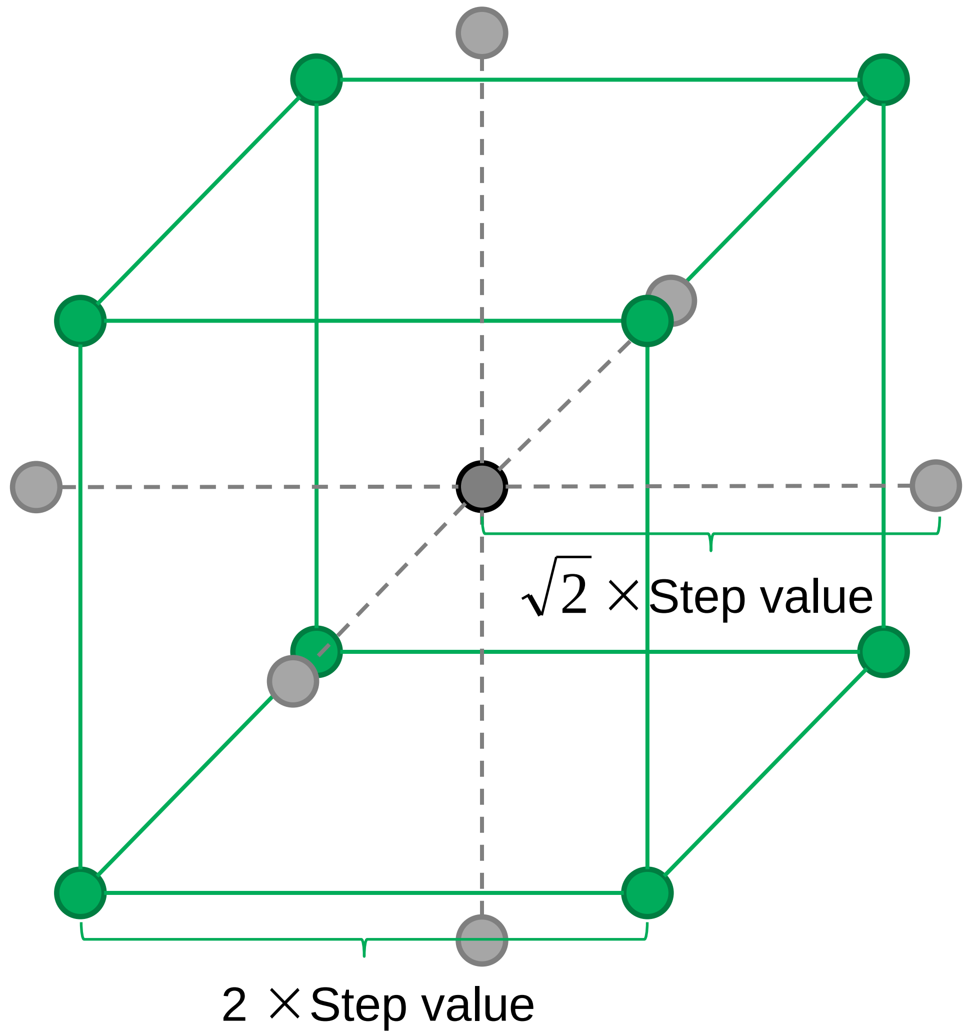


[TS09]

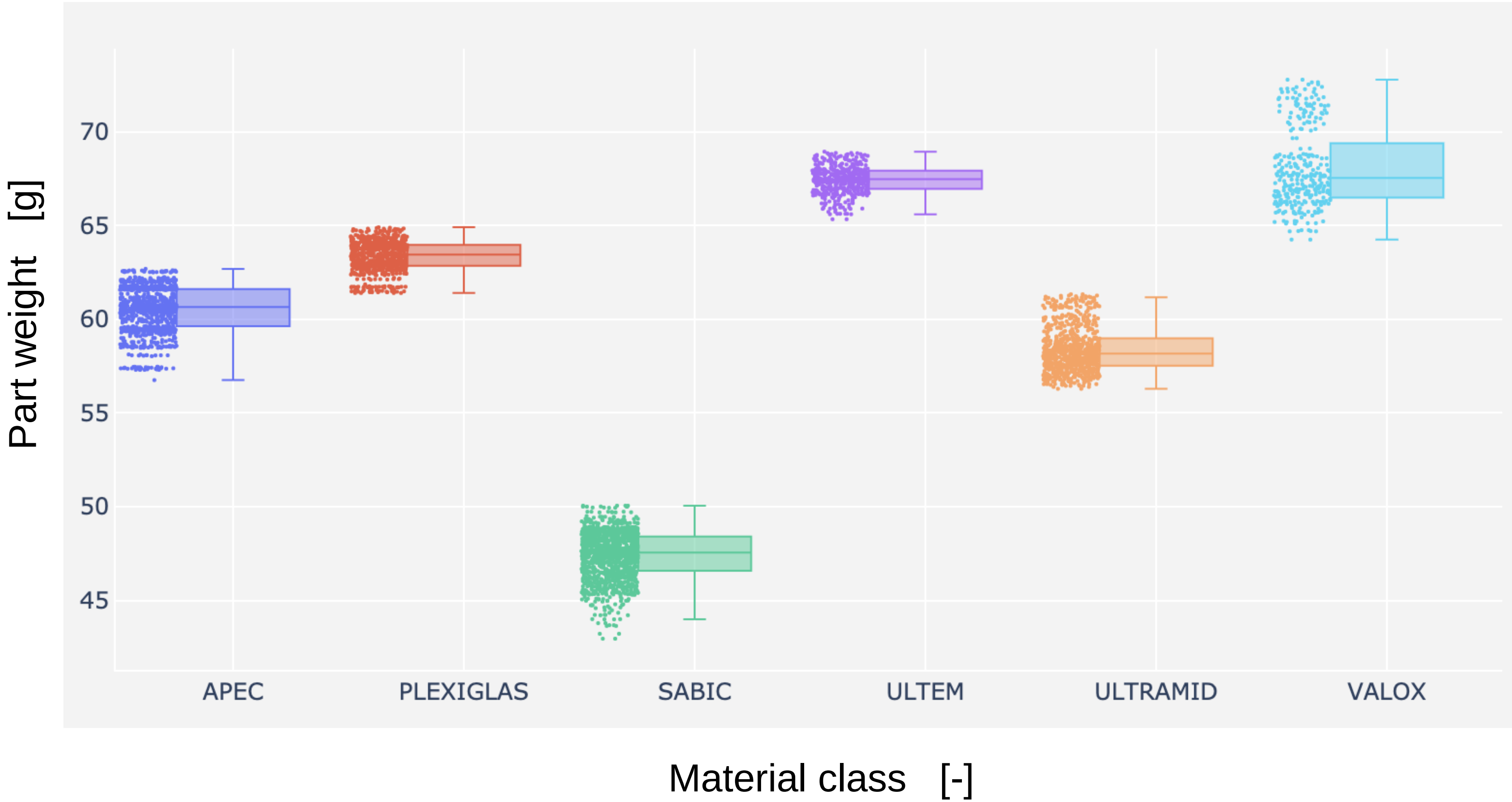
Component dimensions of the 4×2 toy building block



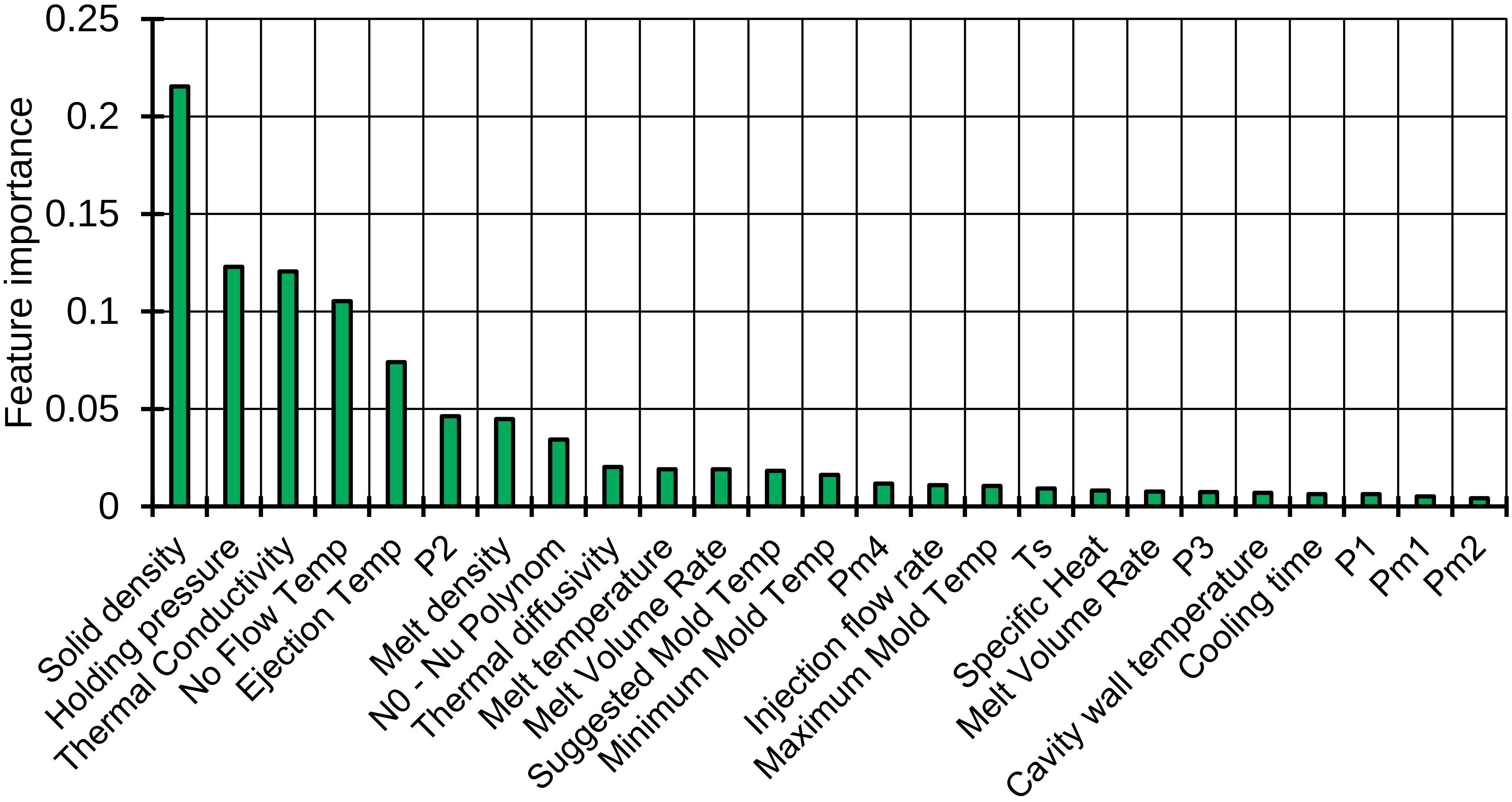
Qualitative depiction of 2^n-Experiment (n=3) plan including star and center point



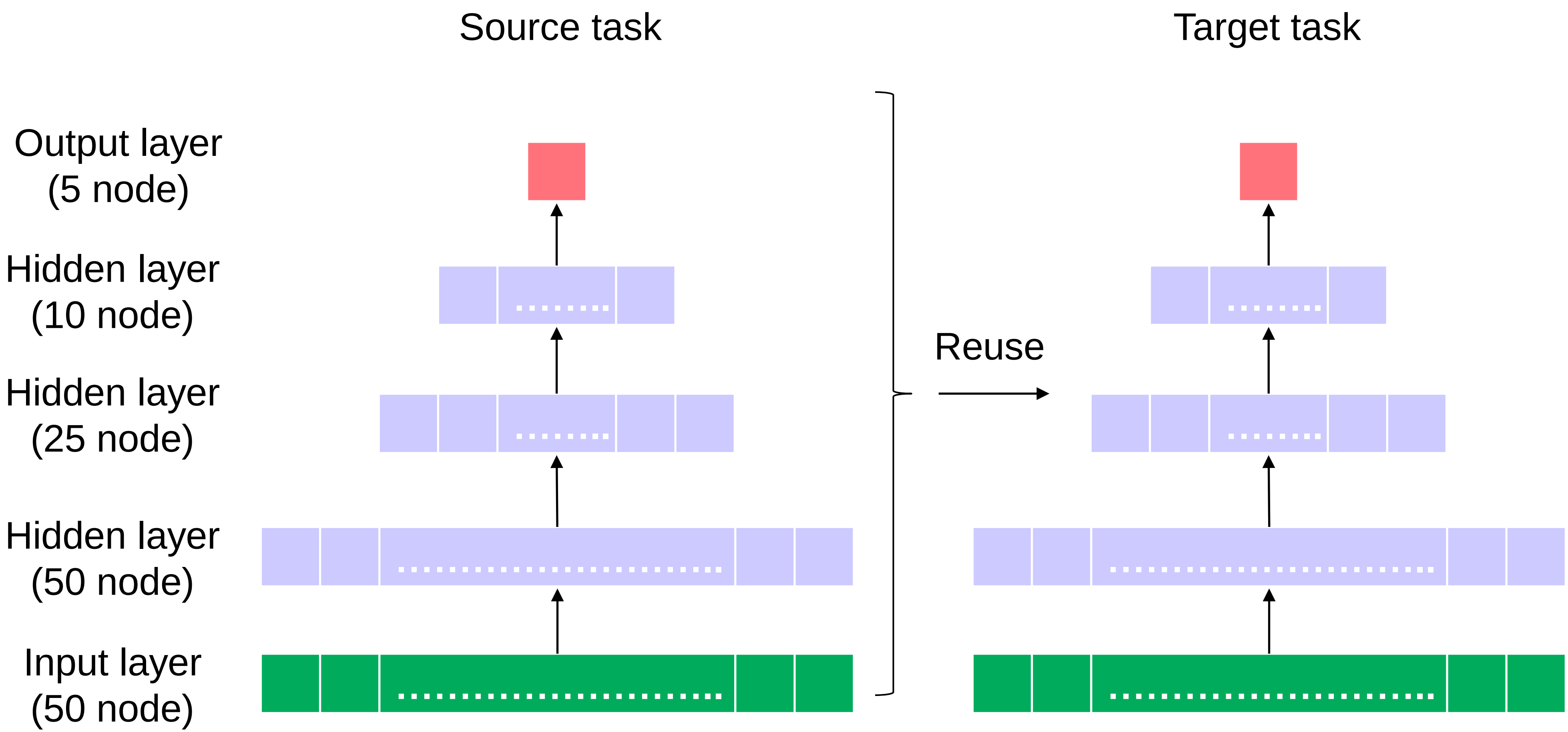
Data visualization of the part weight of the six material classes



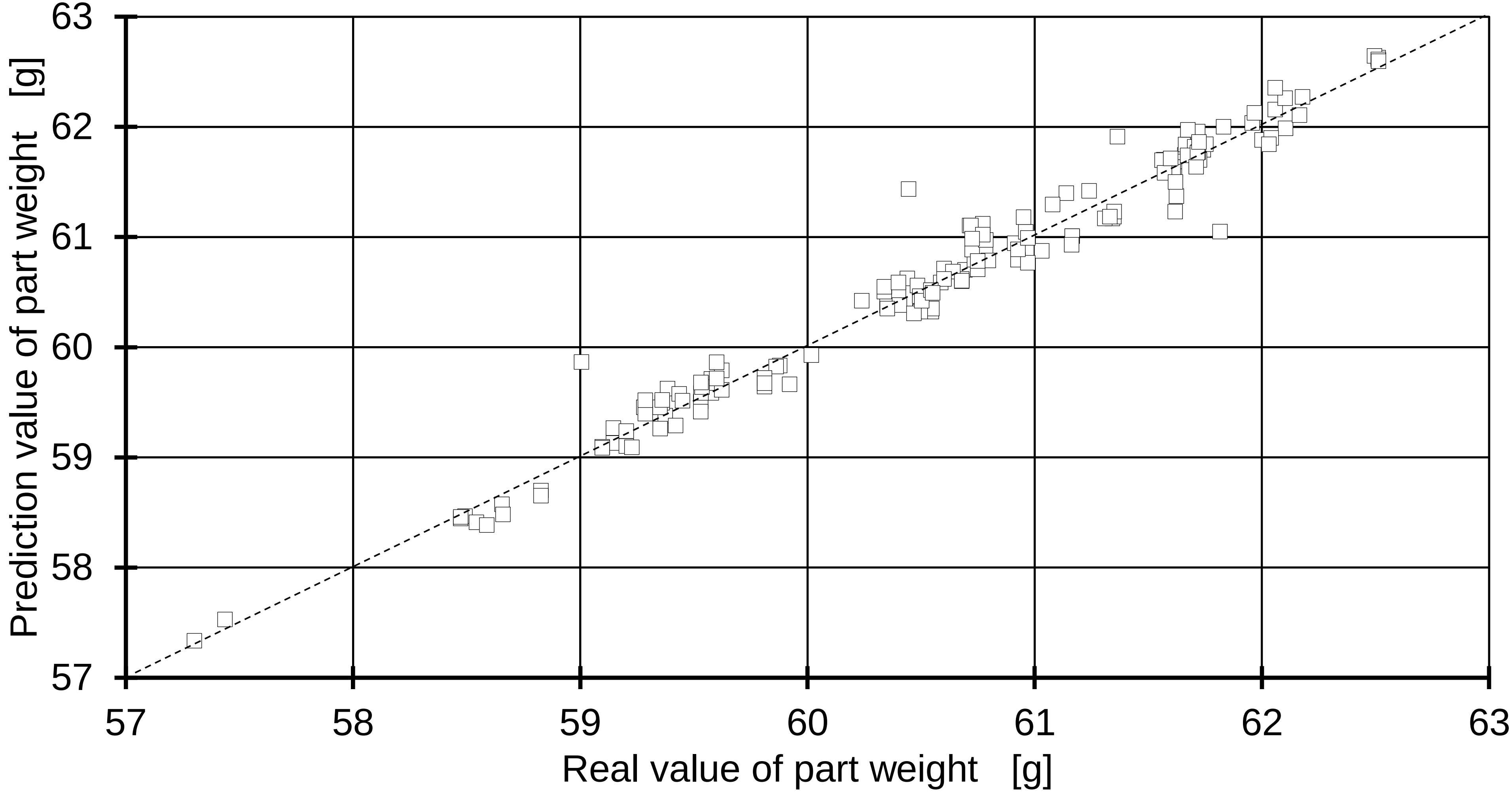
Feature importance score ranking for prediction of part weight



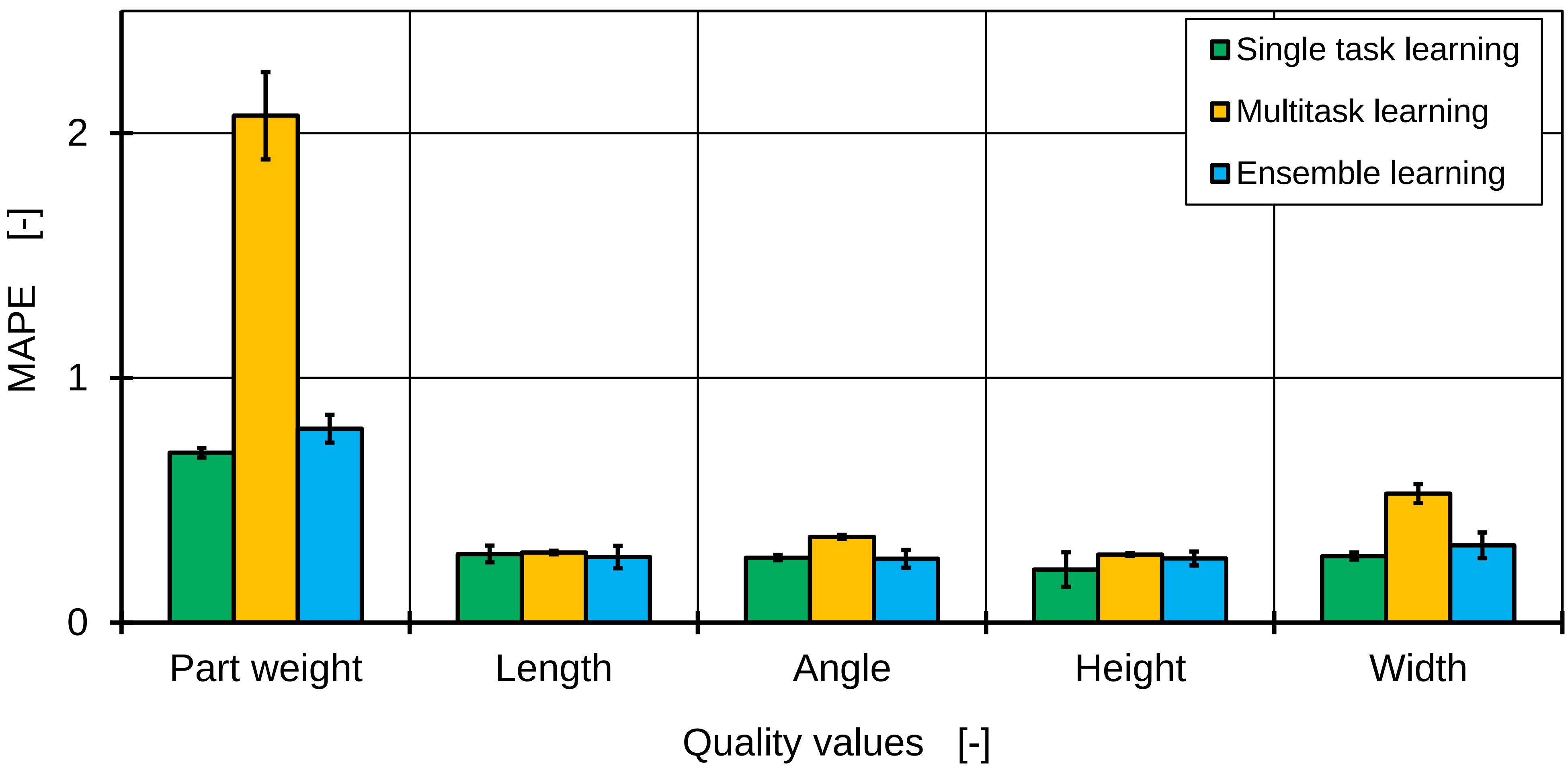
Structure of the deep neural network with transfer learning



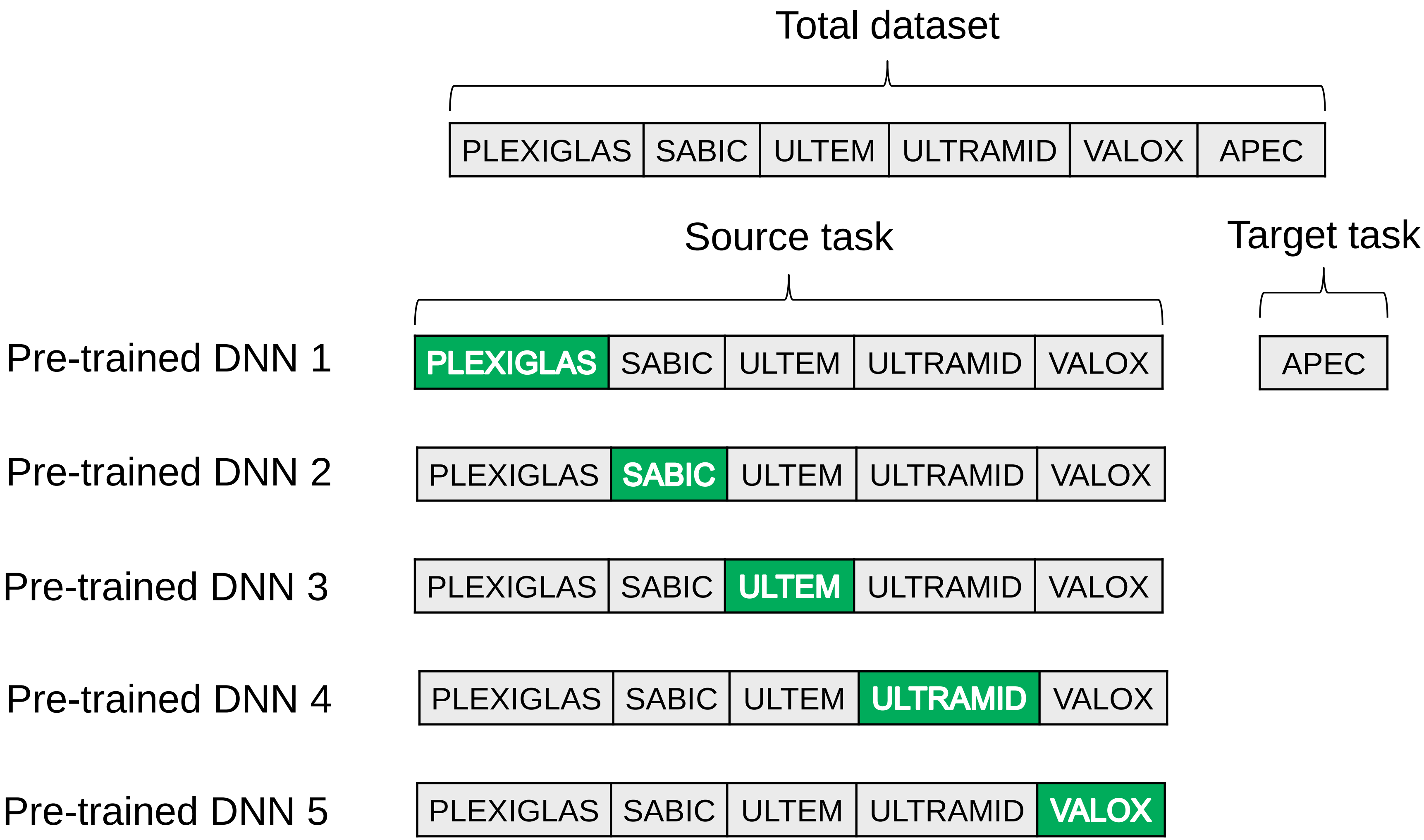
Prediction result of the base model



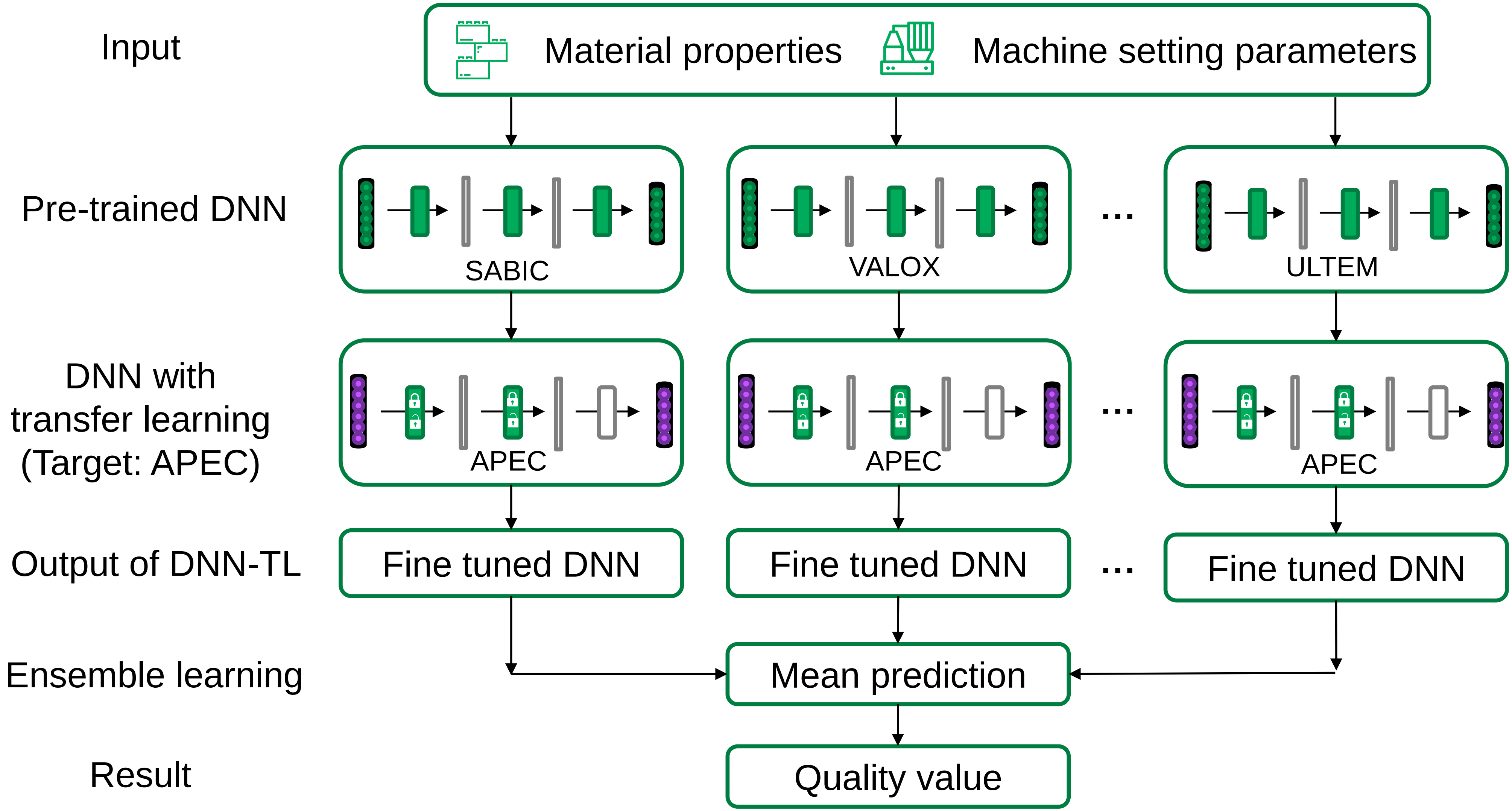
Comparison of single task, multitask and ensemble learning



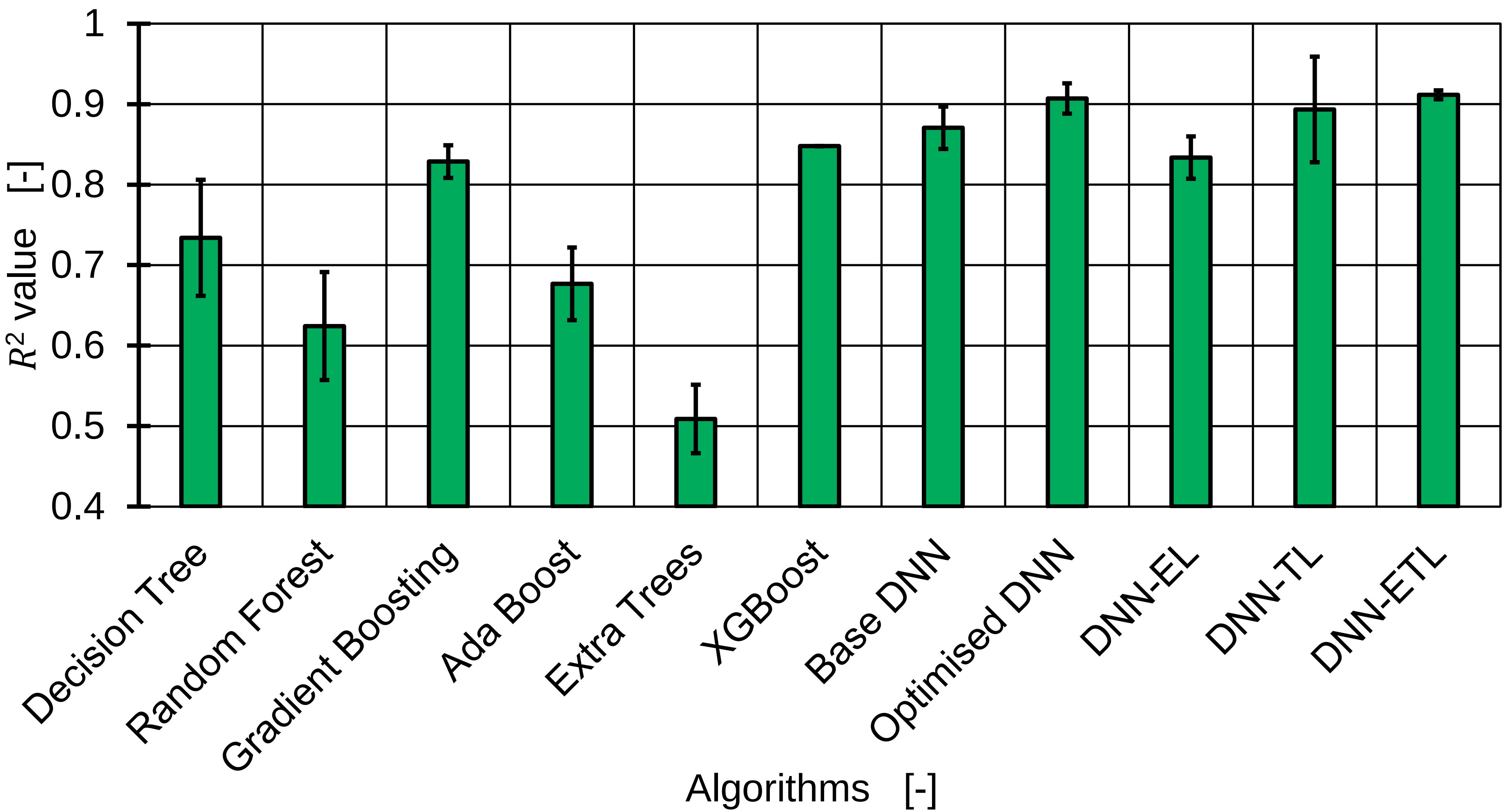
Splitting source task into 5 folds for pre-training DNN models



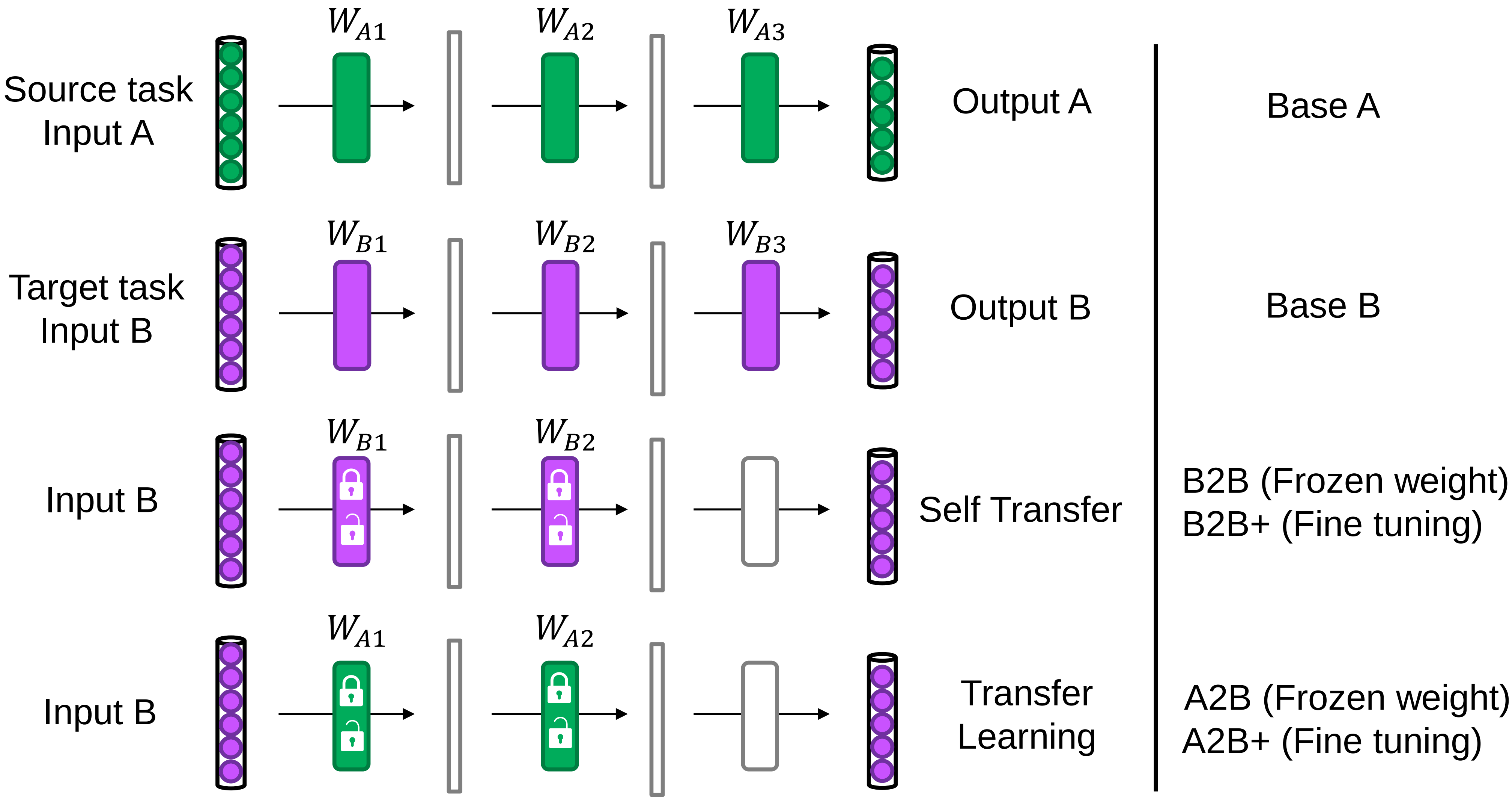
Model structure of transfer learning with ensemble learning



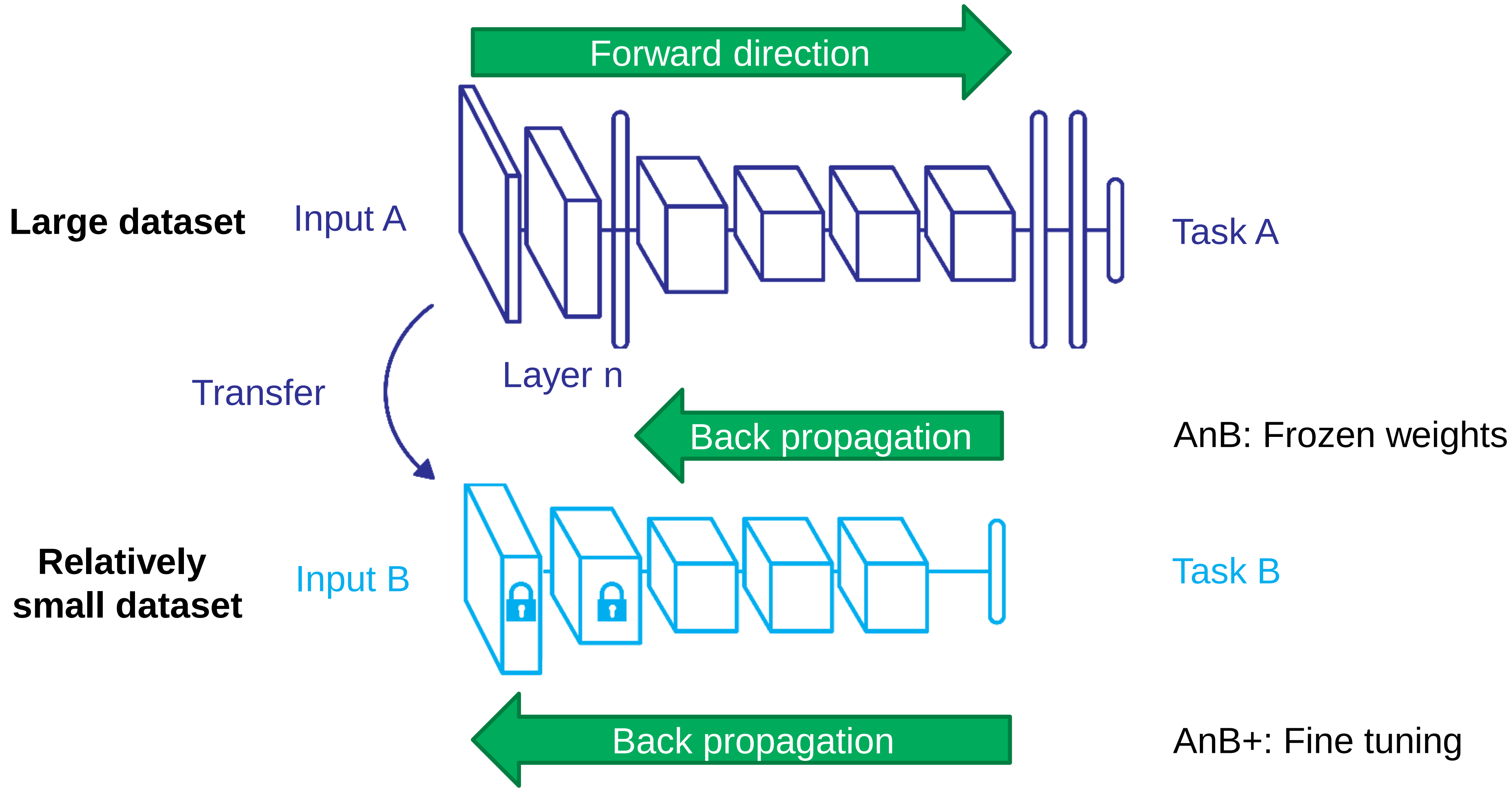
Model comparison of R^2 value



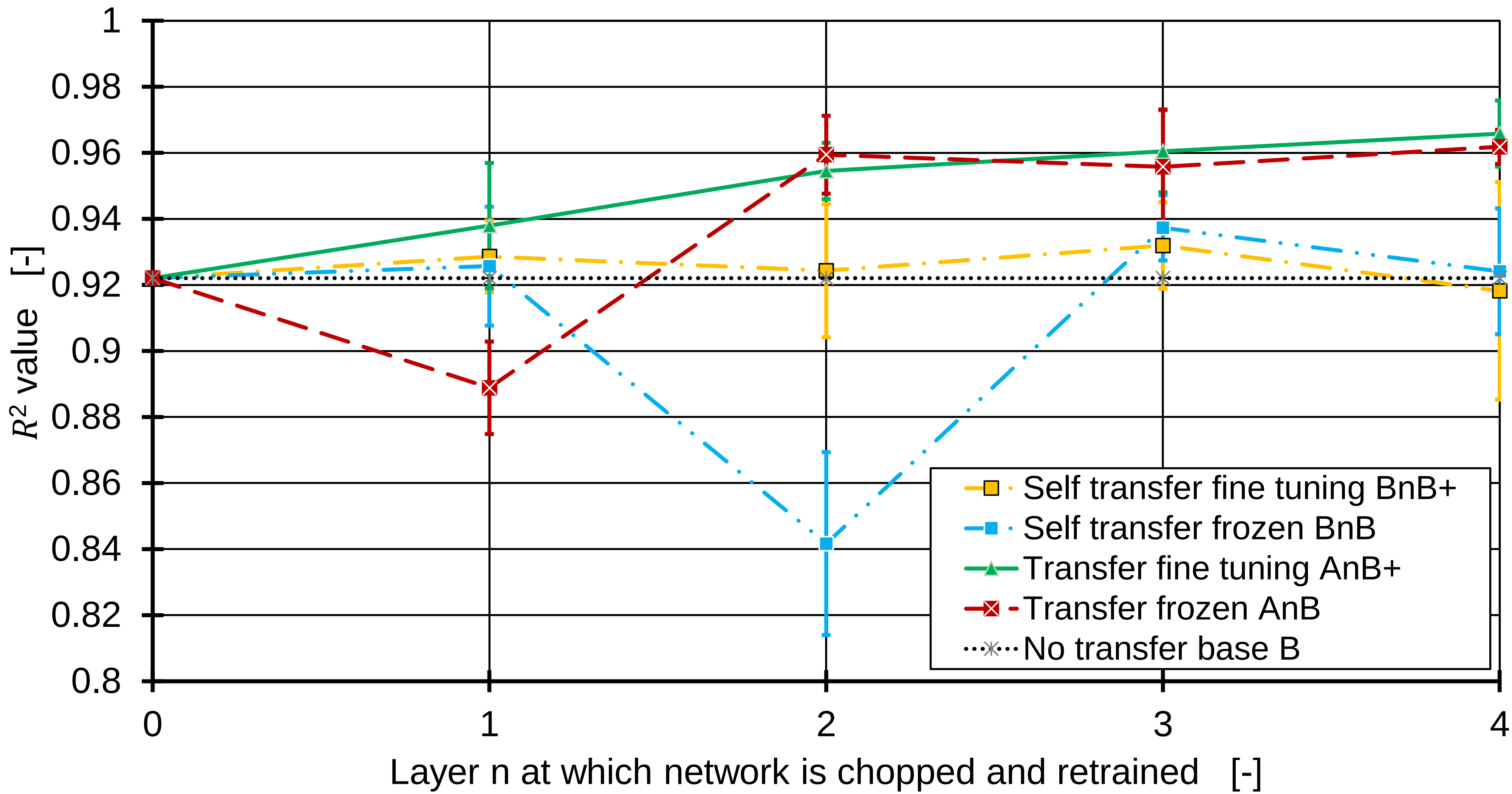
Overview of the experimental treatments and controls



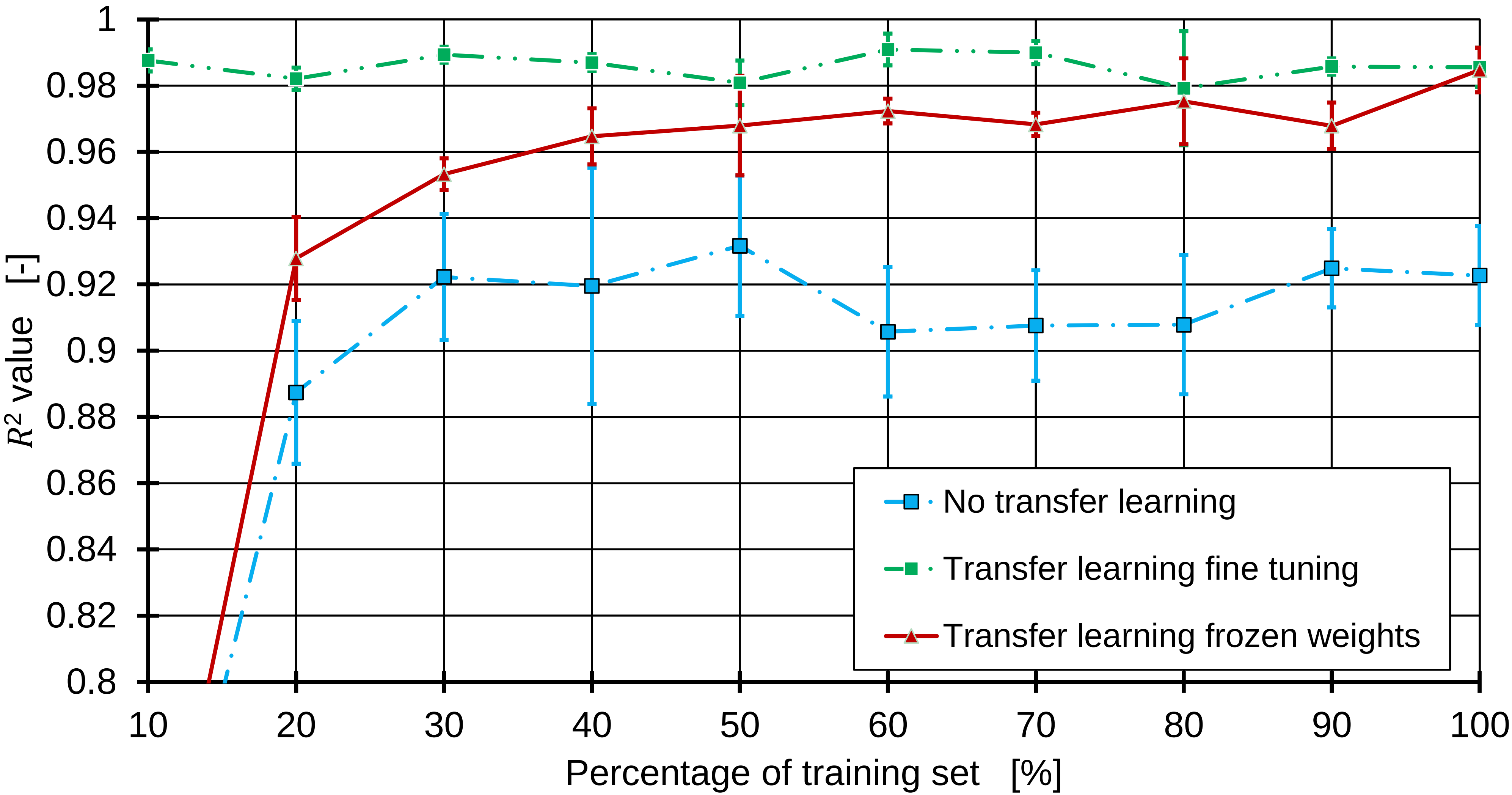
Difference of AnB and AnB+ transfer learning model



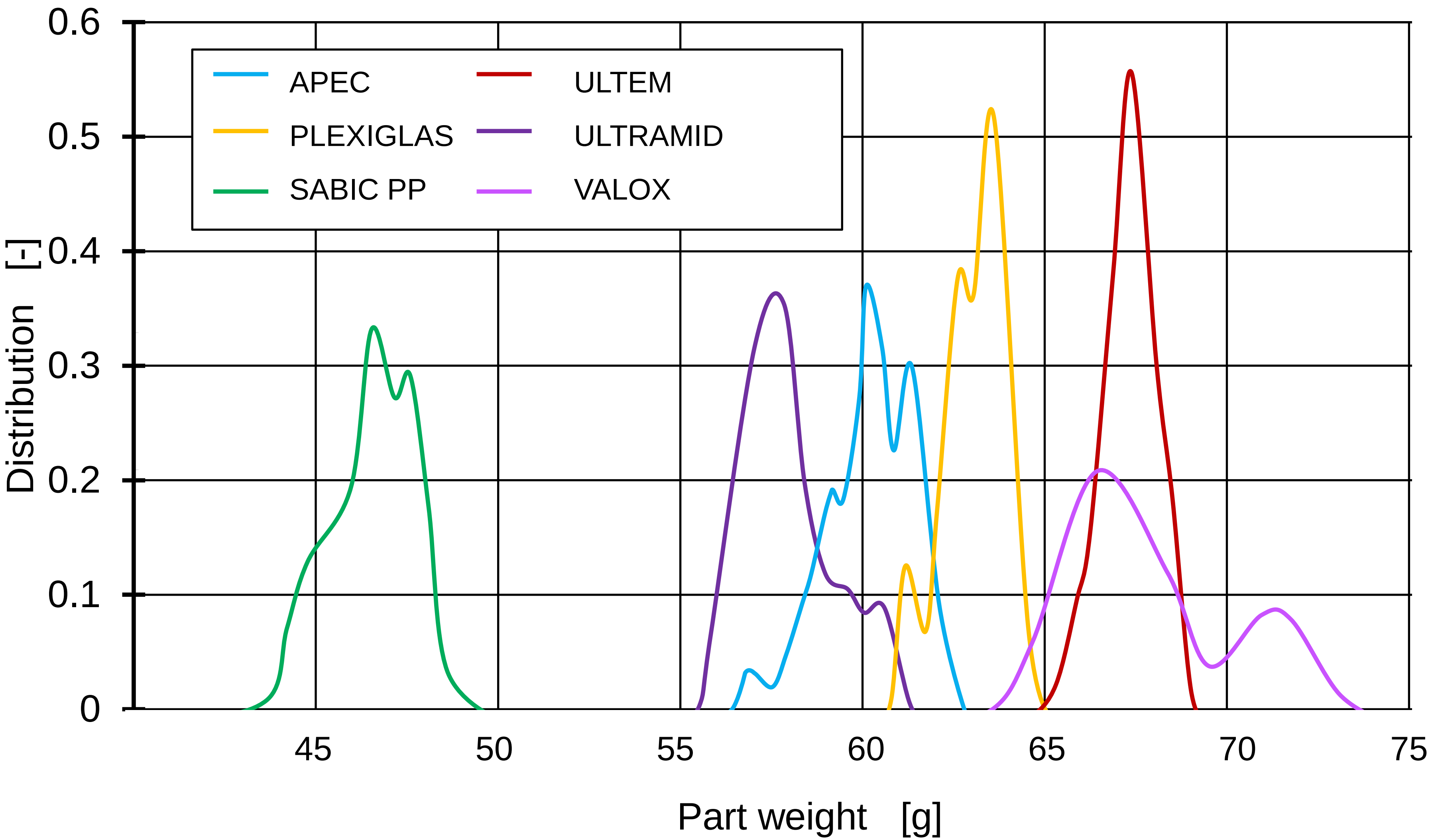
Effect of the number of transferred layers on transfer learning



Effect of the training dataset size on transfer learning



Different part weight distribution of six material classes



Effect of the number of source datasets on transfer learning

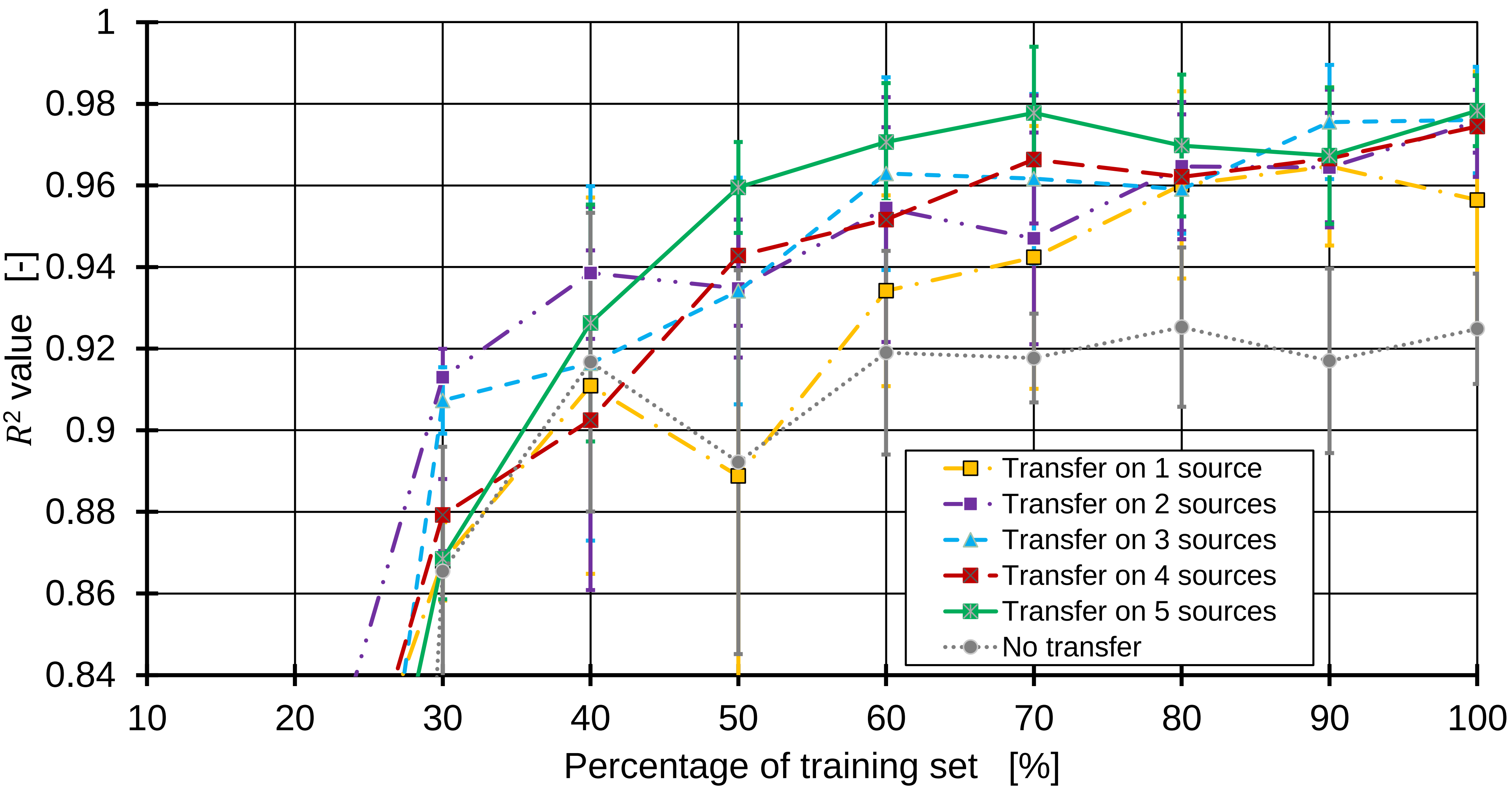


Figure 9.6