Approximate anticipation of base-level reactions by machine learning techniques used to substitute the solving of complex nesting problems

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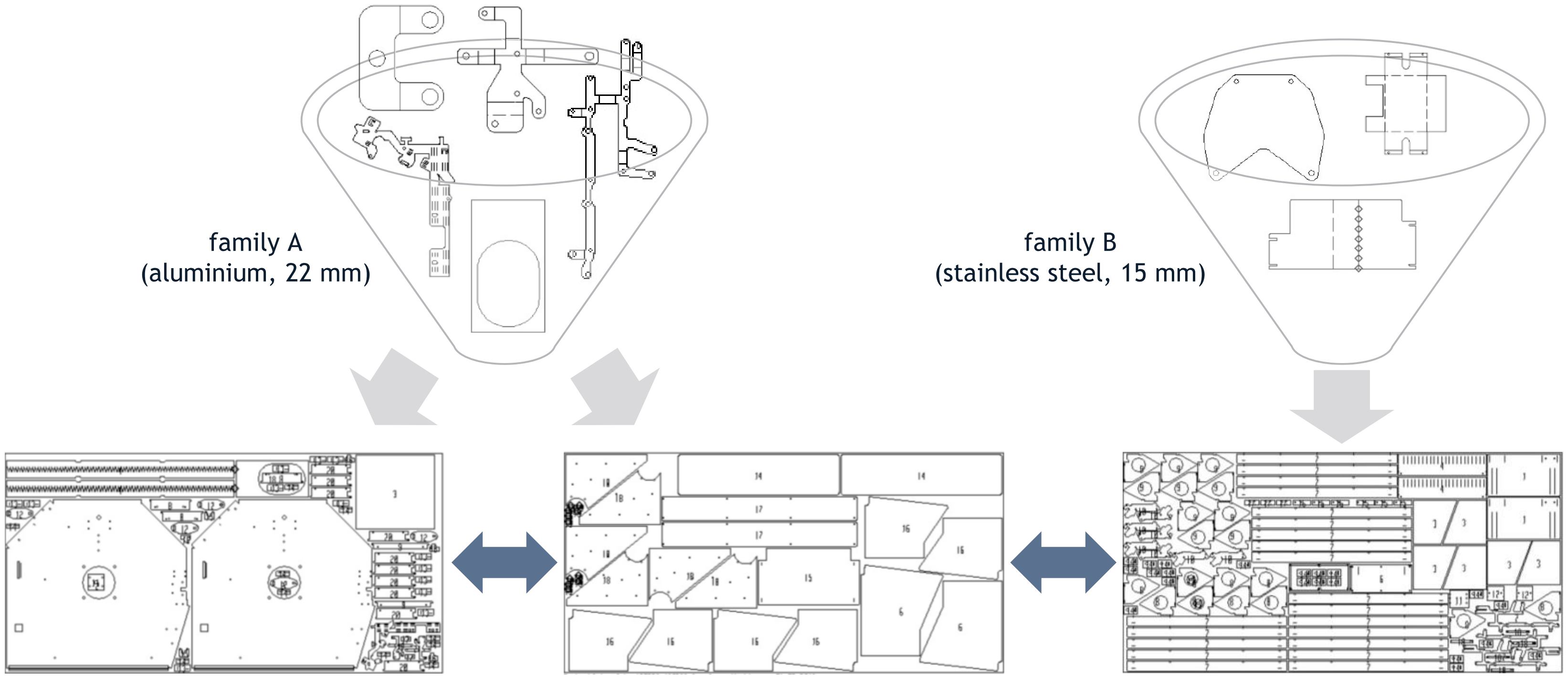
Motivation

- Application case: serial-batch scheduling in the metal-processing industry
  - Laser cutting



Decisions:

1. Batching

   1.1 Capacity-Checking

   ML-Approximation

2. Scheduling

Agenda

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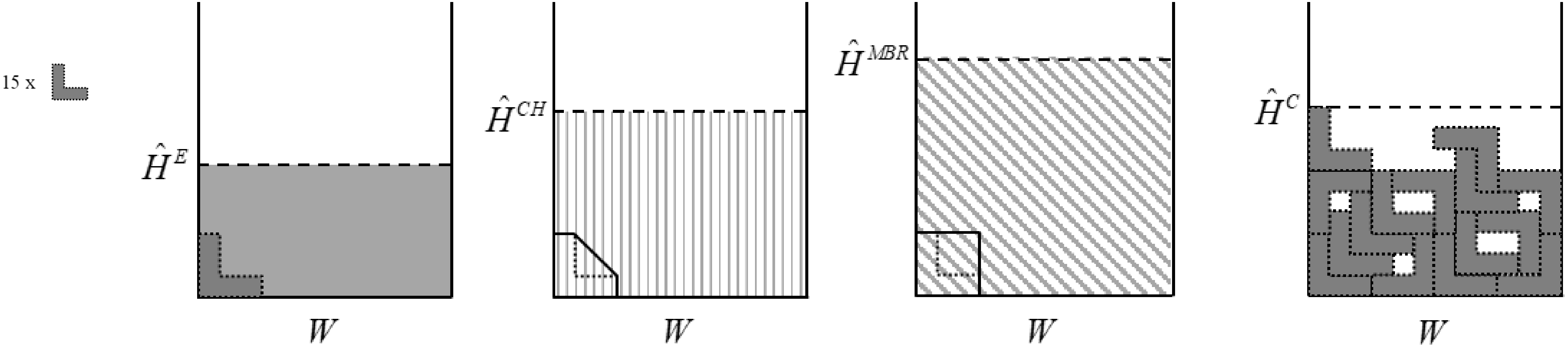
- Simple approximation methods
- Hierarchical integration of the approximate anticipation by machine learning
- Prediction framework
    - Instance generation
    - Feature engineering
- Results

Simple approximation methods

$$\hat{H}^{E} = \max\{\max_{j \in P}\{h_j\}, \sum_{j \in P} a_j^{E} \Big/ W\}$$

$$\hat{H}^{CH} = \max\{\max_{j \in P}\{h_j\}, \sum_{j \in P} a_j^{CH} \Big/ W\}$$

$$\hat{H}^{MBR} = \max\{\max_{j \in P}\{h_j\}, \sum_{j \in P} a_j^{MBR} \Big/ W\}$$



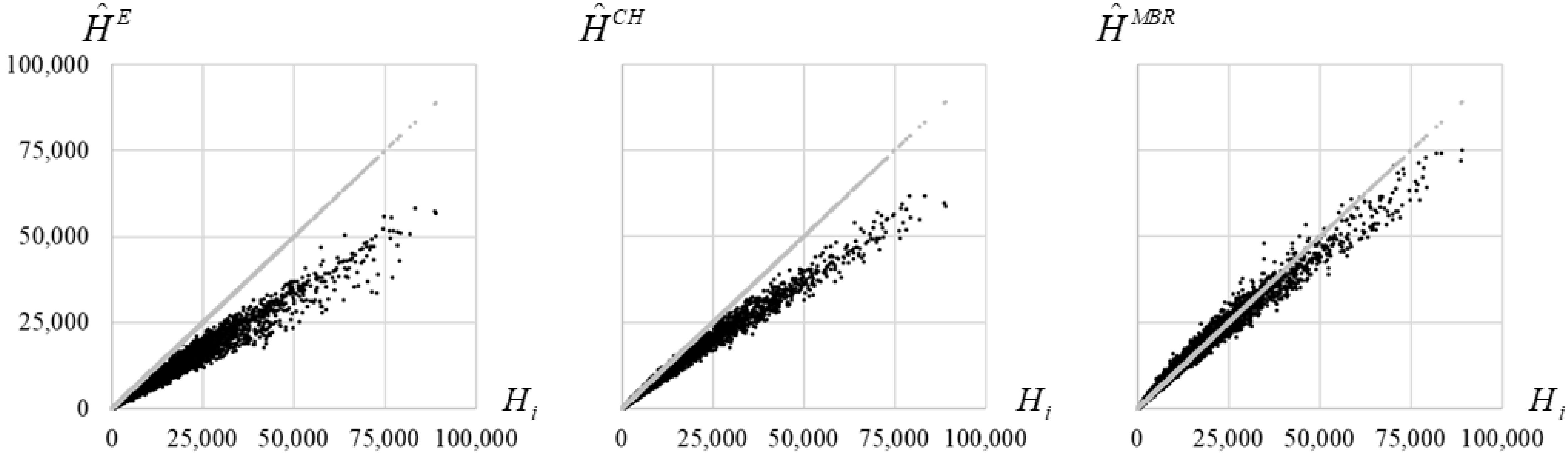
a) Optimistic (SA-E)

b) Conservative I (SA-CH))

c) Conservative II (SA-MBR)

d) computed

Simple approximation methods



a) Optimistic (SA-E)

b) Conservative I (SA-CH)

c) Conservative II (SA-MBR)

Hierarchical integration of the approximate anticipation by machine learning

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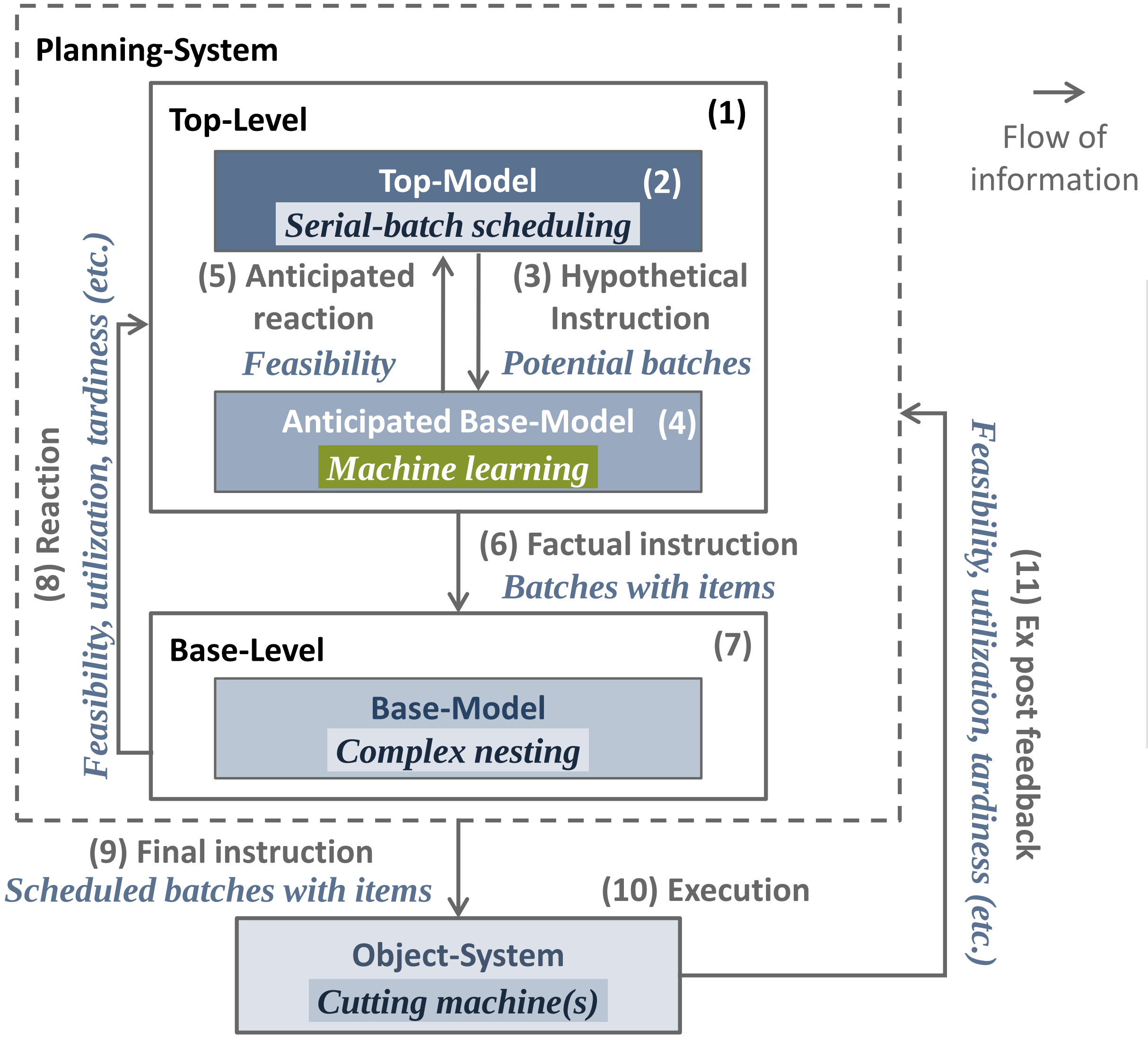
Serial-batch scheduling:

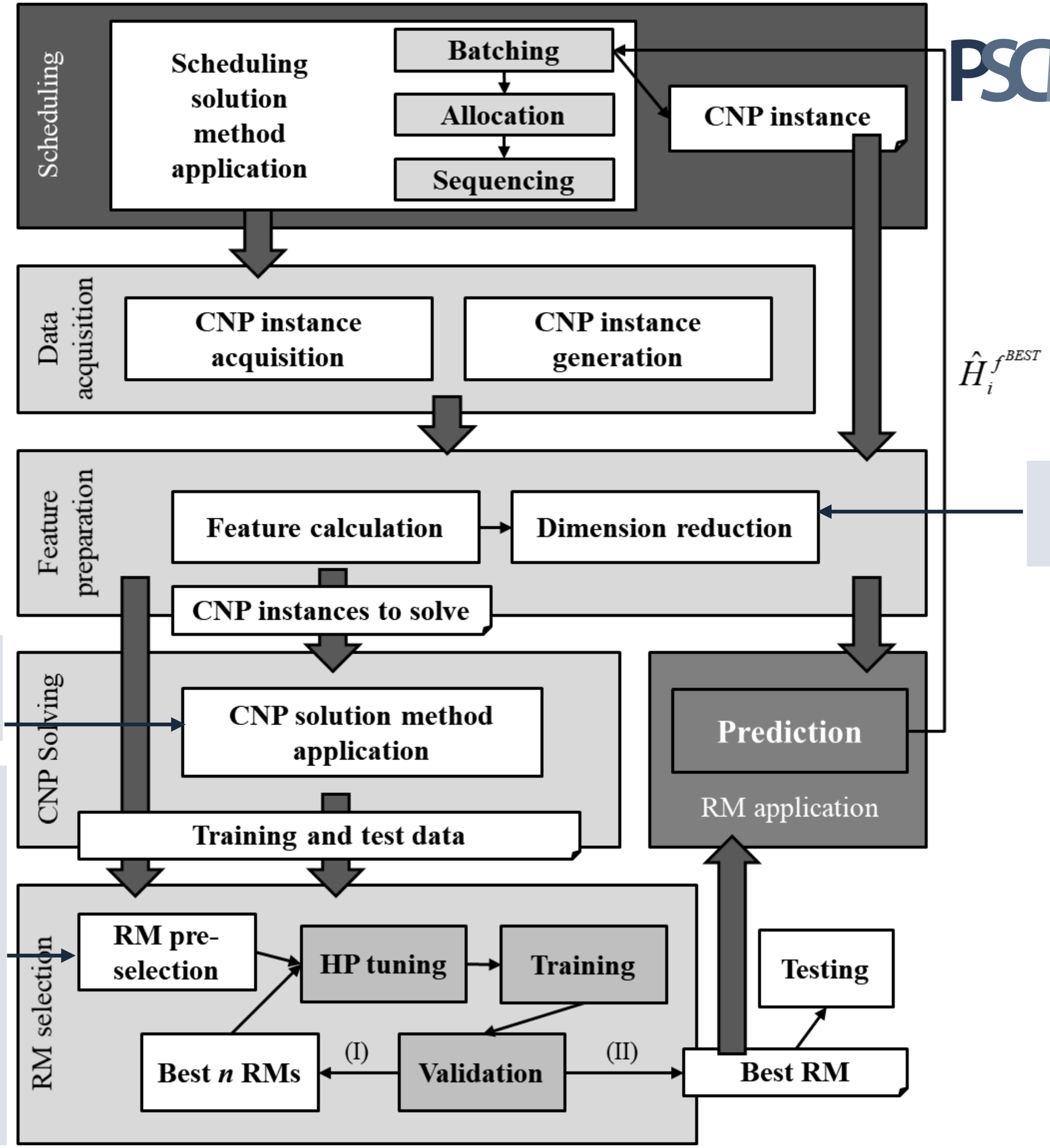
- Batching
- Allocation
- Sequencing



Complex nesting:

- Two-dimensional strip packing problem
- Highly irregular shapes (concave with holes)
- Free rotations

Prediction Framework



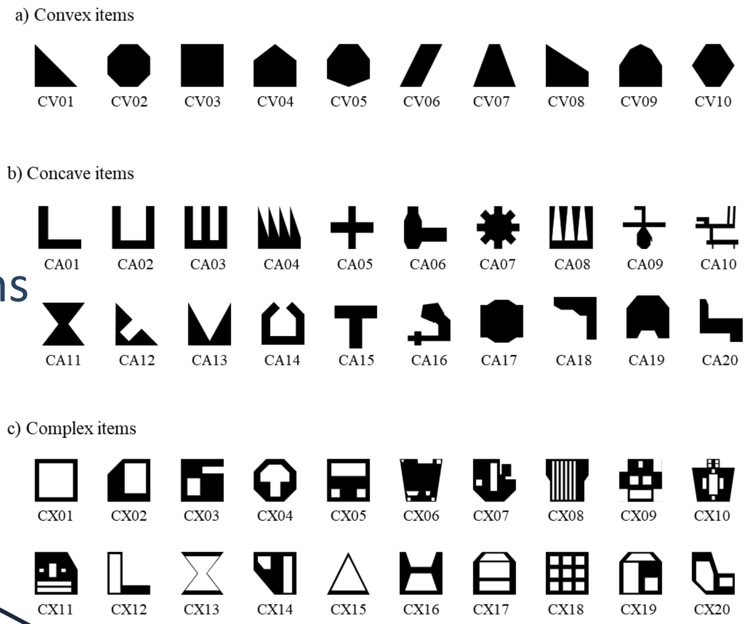
PCA

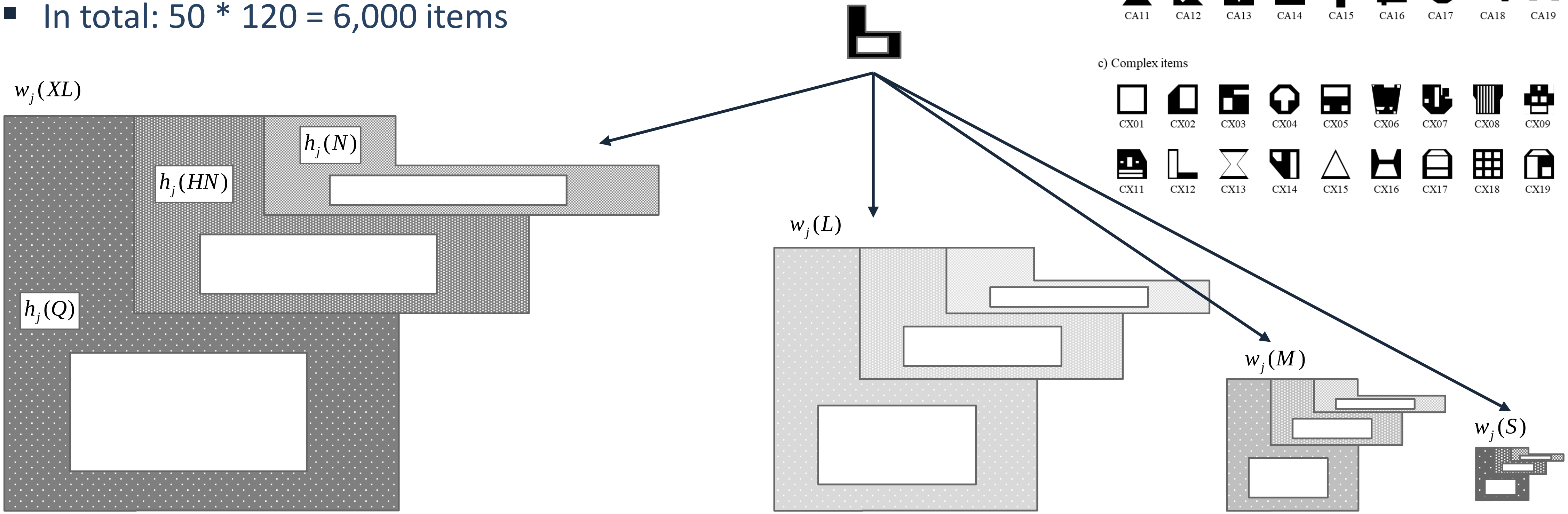
DeepNest

- Linear models, e.g., Ridge regression, Elastic net
- Linear models with polynomial features
- Neighborhood and kernel-based models, e.g., k-nearest neighbors regression, Support Vector Regression
- Decision tree based ensemble methods, e.g., Extremely randomized trees, Bagging regression trees, (Stochastic) Gradient boosted decision trees
- (Deep) Neural networks

Instance Generation

- Generation of complex items based on
  - 50 (10+20+20) elementary items
  - 4 scaling variations in width, 3 in height → 12 scaling variations
  - Every scaling variation is perturbated 10 times → 120 scaling variations
  - In total: 50 * 120 = 6,000 items





Instance Generation

createInstances(N_c := number of instances per class, lb^n, ub^n , *shapeRepository*[ ])

For each $OW \in \{SW, MW, LW\}$ **// object width - 3**

For each $ITA \in \{CV, CA, CX, CV{+}CA, CV{+}CX, CA{+}CX, CV{+}CA{+}CX\}$ **// item type assortment - 7**

For each $ITH \in \{WH, SH\}$ **// item type heterogeneity - 2**

For each $IWA \in \{S{+}M, M{+}L, L{+}XL, S{+}M{+}L, M{+}L{+}XL, S{+}M{+}L{+}XL\}$ **// item width assortment - 6**

For each $IHA \in \{$Q, HN, N, Q+HN, Q+N, HN+N, Q+HN+N$\}$ **// item height assortment – 7**

For i = 1 to N_c = 50 **// for each of the 1,764 instance classes; in total: 88,200 CNP instances**

$beta^R_{ITA}$:= ~U(*BD*); $beta^R_{IWA}$:= ~U(*BD*); $beta^R_{IHA}$:= ~U(*BD*);

$attPerm_{ITA}$:= *getPerm*(*ITA*); $attPerm_{IWA}$:= *getPerm*(*IWA*); *attP*

S[ ] := getShapeSubsets (*shapeRepository*[ ], *ITA*, *ITH*, *IWA*, *IHA*)

n := ~$U\,(lb^n = 50, ub^n = 150)$

For j = 1 to n

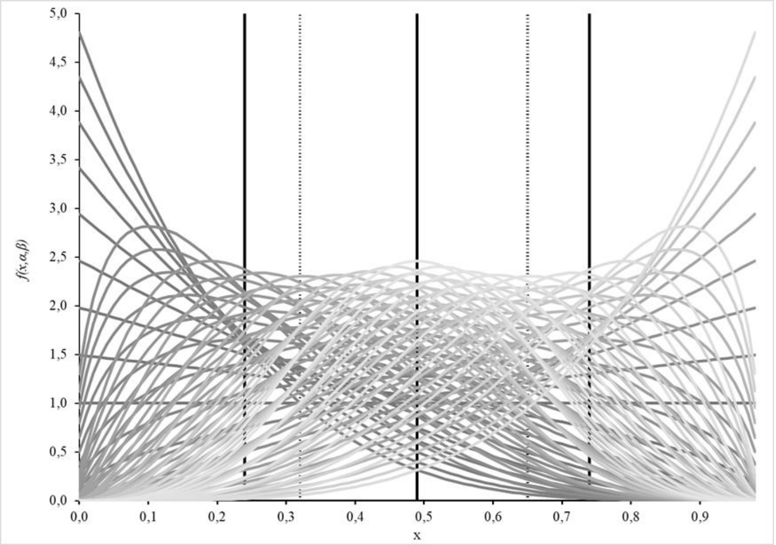
$type_j$:= getTypeAttribute ($beta^R_{ITA}$, $attPerm_{ITA}$, *ITA*); **// e.g**

w_j := getWidthAttribute ($beta^R_{IWA}$, $attPerm_{IWA}$, *IWA*); **// e.g**

h_j := getHeightAttribute ($beta^R_{IHA}$, $attPerm_{IHA}$, *IHA*); **// e.g.**

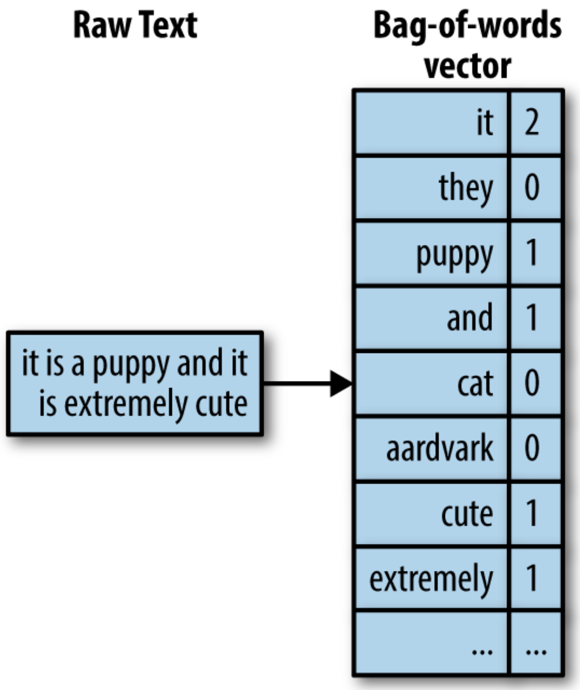
item := *selectItemFromSubset* (*S*[ ], $type_j$, w_j, h_j)

addItemToInstance (*item*);



Feature engineering

- Problem Instance Encoding: Aggregated Geometrical Representation instead of "Bag-of-Words"
- Geometrical Representation: Sum of Area (and variations), Number of vertices …
- Advantage: more flexibility in terms of input dimension
  - Machine Learning Model can be used even for instances with new items
  - Dimension reduction methods can be used straightforward



Feature engineering

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- Basic instance features
  - 43 item properties (like h_j, $r_j^{CH} = a_j^{CH} / a_j^{MBR}$ - rectangularity of the convex hull, $n_j^{XIA-IA} = n_j^{XIA} / n_j^E$ - rel. number of reflex interior angles, …)
  - Aggregation function for calculating instance features: *SUM*, *MED* (median), *MIN*, *MAX*, *VAR* (variance), *Q1* (first quartile), *Q3* (third quartile), *P10* (10% percentile), *P90* (90% percentile), and *SKEW* (Fisher-Pearson coefficient of skewness).

  → 430 features
- Additional instance features (22):

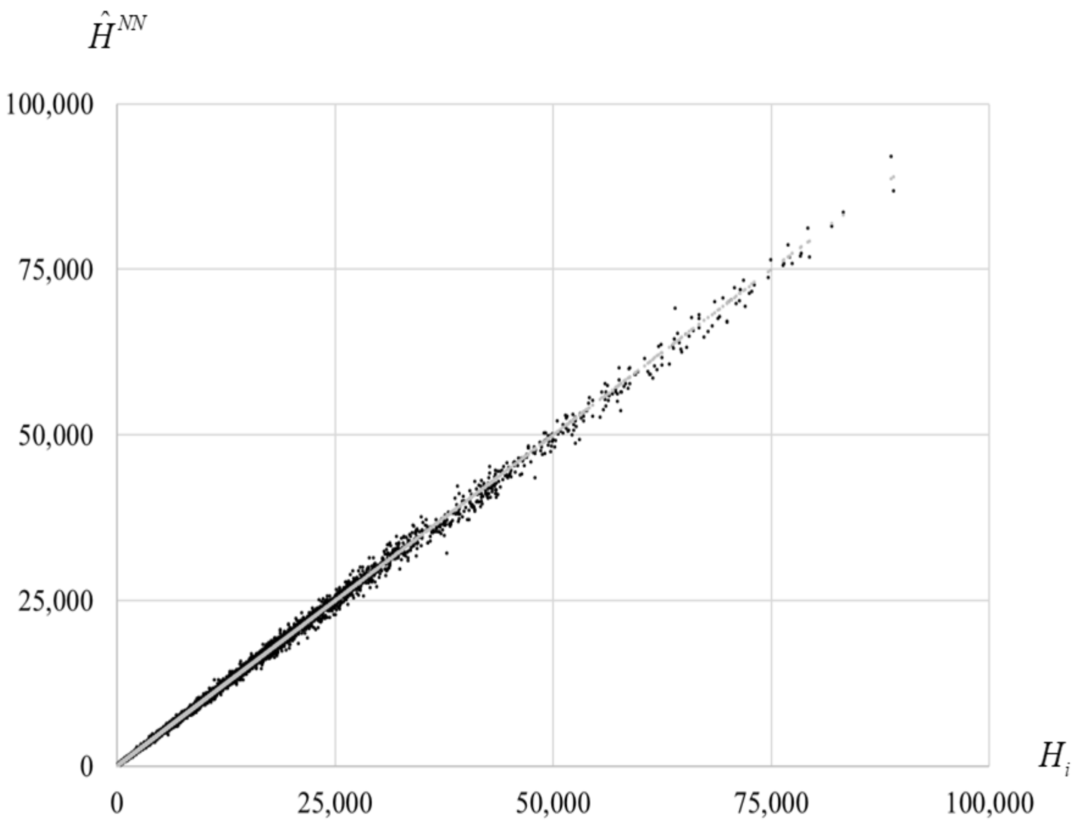
→ 452 instance features (TIF)
→ reduced set with 189 features (RIF) without computationally complex features

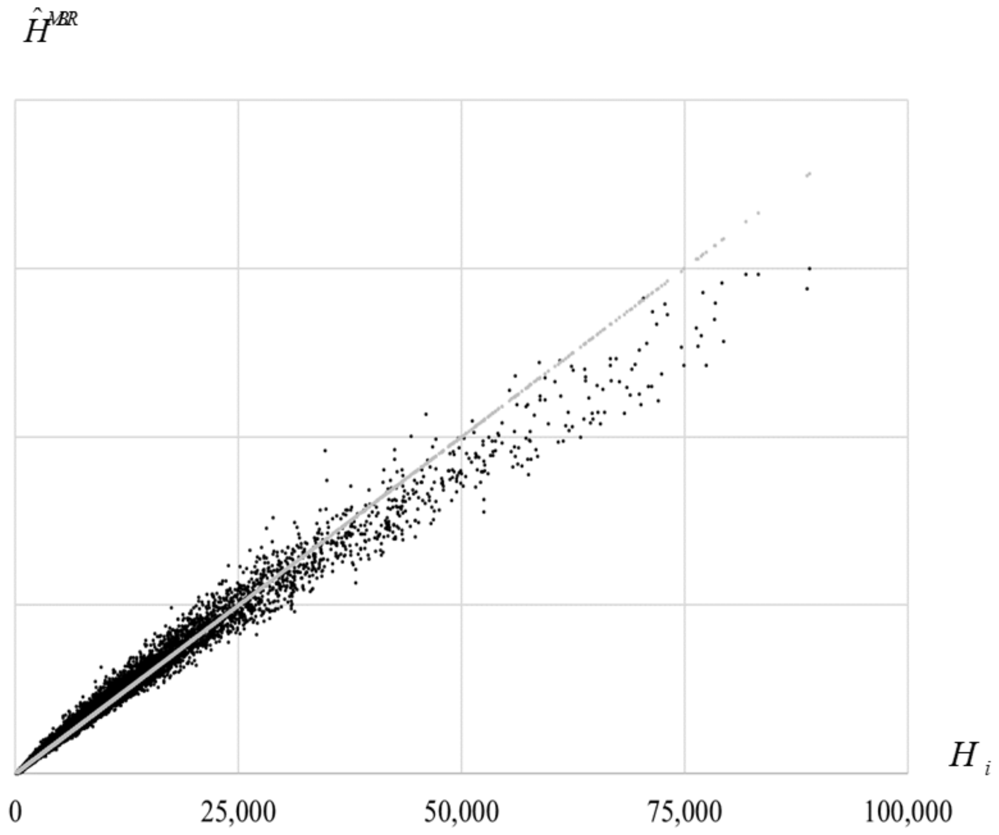
Feature	Description
n	Total number of items
W	Width of the strip
$\hat{H}^E$	Predicted height based on the area of the enclosing polygon
$\hat{H}^{CH}$	Predicted height based on the area of the enclosing polygon's convex hull
$\hat{H}^{MBR}$	Predicted height based on the area of the enclosing polygon's MBR
n^D	Number of different item categories; two items have a different category if they are not completely identical regarding the combination of the attributes $BT \in \{CV, CA, CX\}$, $IW \in \{S, M, L, XL\}$, and $IH \in \{Q, HN, N\}$.
$h = n^D/n$	Heterogeneity of items
$MIN^{\#IpC}$	Minimum number of items regarding all item categories
$MAX^{\#IpC}$	Maximum number of items regarding all item categories
$MEAN^{\#IpC}$	Mean of the number of items regarding all item categories
$MED^{\#IpC}$	Median of the number of items regarding all item categories
$VAR^{\#IpC}$	Variance of the number of items regarding all item categories
$SKEW^{\#IpC}$	Skewness of the number of items regarding all item categories
$Q1^{\#IpC}$	First quartile of the number of items regarding all item categories
$Q3^{\#IpC}$	Third quartile of the number of items regarding all item categories
$P10^{\#IpC}$	10% percentile of the number of items regarding all item categories
$P90^{\#IpC}$	90% percentile of the number of items regarding all item categories
p^{LI}	Percentage shares of large items ($w_j \geq 0.75 \cdot W$); *
p^{SI}	Percentage shares of small items ($w_j \leq 0.25 \cdot W$); *
p^{HR}	Percentage shares of items with a high rectangularity ($r_j^E > 0.9$); *
p^{LR}	Percentage shares of items with a low rectangularity ($r_j^E \leq 0.5$); *
p^{NCON}	Percentage shares of non-convex items (items with $n_j^{XIA} > 0$)
p^{COMP}	Percentage shares of complex items (items with $n_j > 1$)

Results

RM	RIF		TIF	
	RMSE	mean CT [seconds]	RMSE	mean CT [seconds]
Polynomial elastic net (PEN)	471.58	42.19	383.96	240.40
Bagging regression tree with PEN	470.84	3,284.89	383.22	17,082.95
Neural network	374.96	6,135.63	**339.17**	56,569.90
SA-MBR	1,230.48 [RMSE]			

Results


$\hat{H}^{NN}$
100,000
75,000
50,000
25,000
0
0
25,000
50,000
75,000
100,000
H_i


$\hat{H}^{MBR}$
0
25,000
50,000
75,000
100,000
H_i

Conclusions

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		Over-estimations	Underestimations below or equal 5%	Underestimations below or equal 10%
SA-MBR		62.4%	79.2%	89.9%
NN with PCA(98%), “DiffLab”, and	RIF	60.8%	92.9%	98.6%
	TIF	58.5%	93.4%	98.8%

- Outlook
  - Prediction Intervalls → Uncertainty Quantification, Bayesian methods
  - Extension to 3D-Nesting: Capacity Checking, Batch Processing Time
  - How to include the ML-model into the hierarchical problem?

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Thank You For Your Attention