Introduction to Transfer Learning

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Outline

- Traditional Machine Learning
- Motivation
- Definitions
- Research Issues
 - Transfer Learning Hierarchy
- Challenges
- Heterogeneous Transfer Learning
- Actual Work

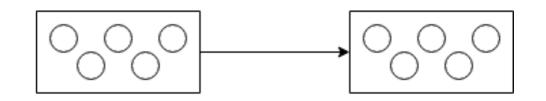


A Major Assumption in Traditional Machine Learning

Training and test (future) data come from the same task and the same domain:

- Represented in the same feature and label spaces.
- Follow the same distribution.

Class	Age	Sex	Survived
3rd	adult	male	0
crew	adult	male	1
3rd	child	male	0
1st	child	female	1

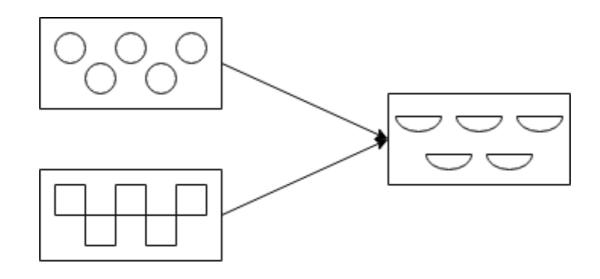




In Real-world Application

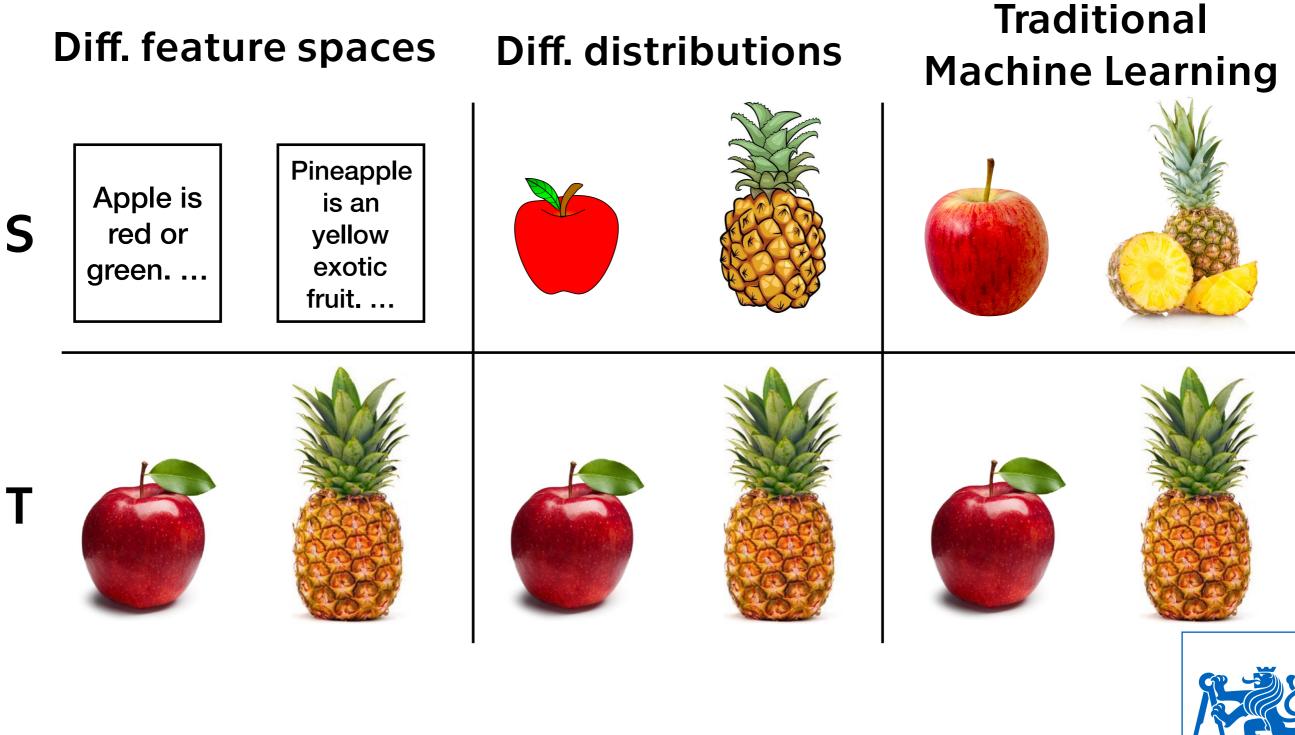
Training and test (future) data may come from different domains and different tasks, which have:

- different marginal distributions or different feature spaces,
- different predictive distributions or different label spaces.

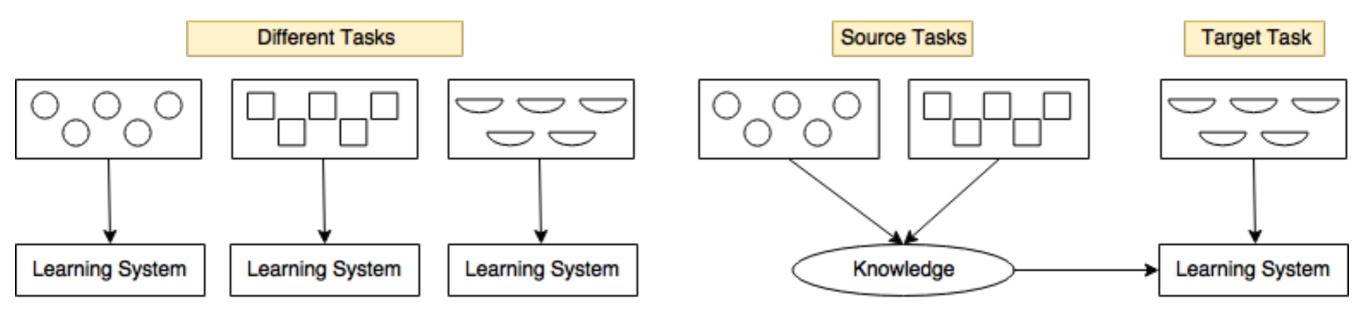




Data Representation



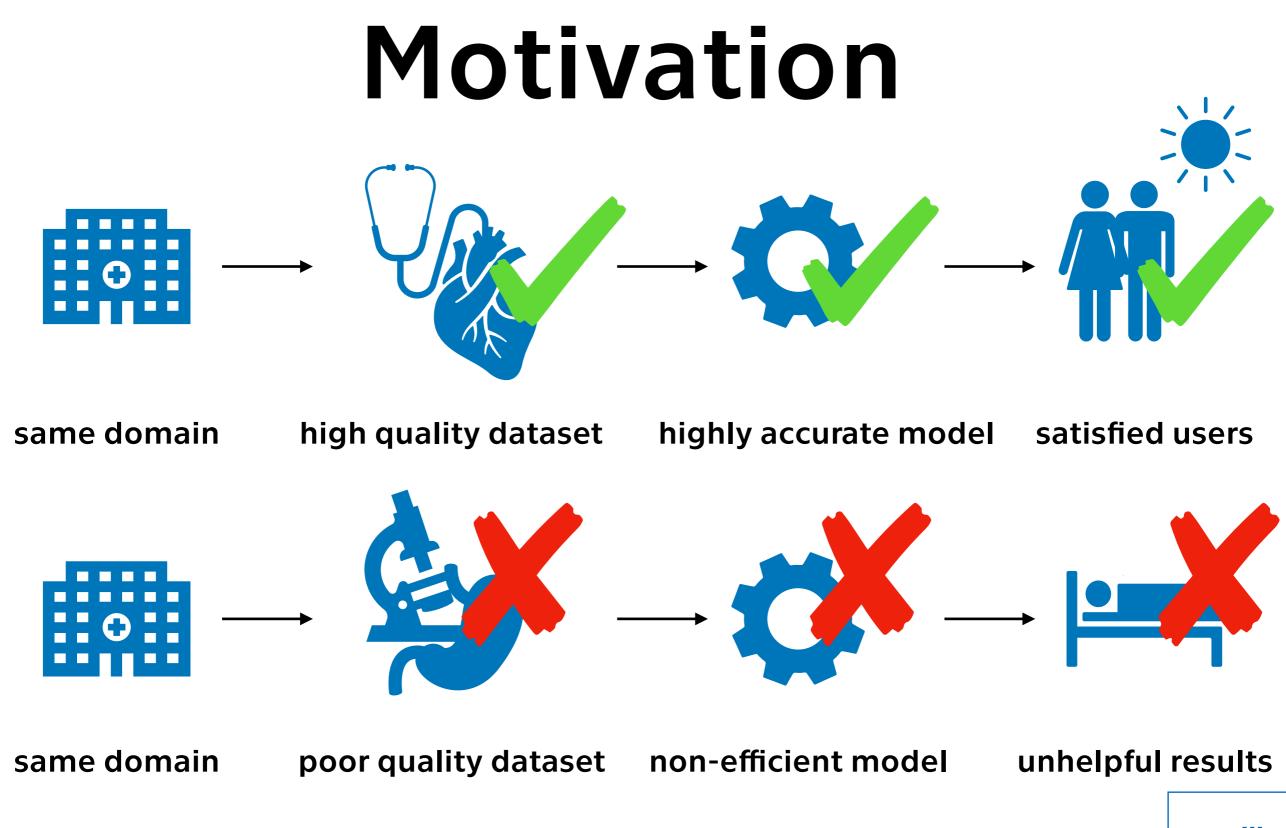
Traditional Machine Learning versus Transfer Learning



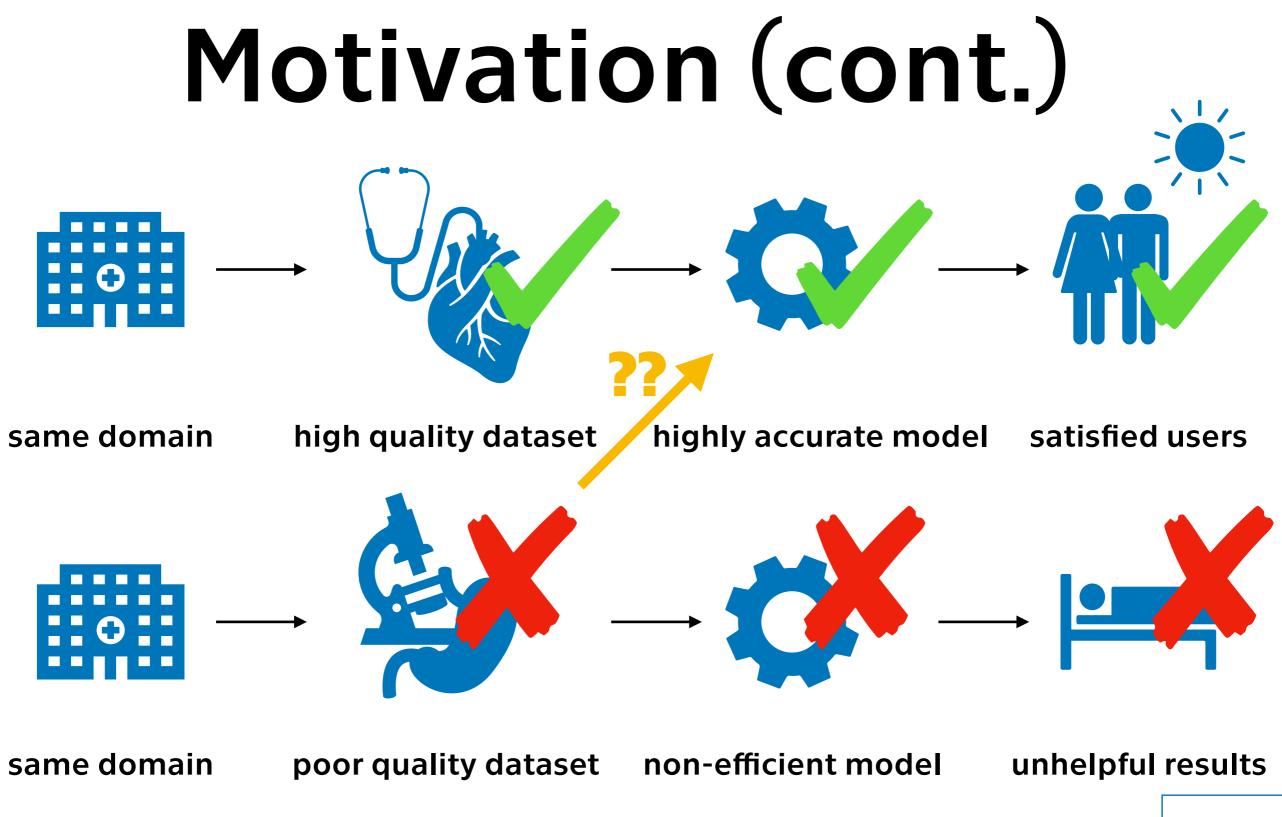
Learning process of Traditional Machine Learning.

Learning process of Transfer Learning.











Motivation (cont.)

real dataset - cancer detection

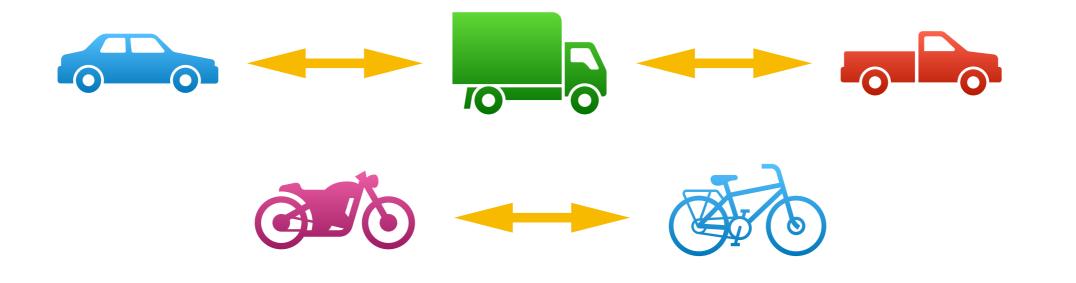
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72			27.3.1933 22.10.1973		1	1	3	3	1		21		>1,02	1,14 > 1 1,72 > 1	15 1,22	2 > 1,03 > 1,03	-26	0 34,1	1 2	3,3 5,64		27,6	21,46 157,51	52,08 152,53	73,54 310,04	21,86 237,47		1,43 1 15,2 10	42 6	0 175	376 2468	6 236 8 1397		421	50
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106			23.9.1964	50	0	1	2		2		1.	2 1,02	>1,08		1,03	>1,03	7	0 3,4	9 0	1,74			10,32	3,73	14,05	2,6	0,81 3	3,41							
108			23.8.1970 15.5.1981		3	1	1	3 1			2	4 1,04 6 1,11		1.38 >1.2	1,02	≥1,03 ≥1,07	-60	1 6,7		1,18			3,33	7,15	10,48 30,74	1,18 64.25	1,05 2	1,23							
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Transfer Learning

Transfer learning definition:

The ability of a system to recognize and apply knowledge and skills learned in previous tasks/domains to novel tasks or new domains, which share some commonalities.





Definitions

Definition 1. A domain D is a two-tuple (X, P(X)), where X is the feature space of D and P(X) is the marginal probability distribution where $X = x_1, ..., x_n \in X$.

Definition 2. A task T is a two-tuple (Y, f()) for some given domain D. Y is the label space of D and f() is an objective predictive function for D. f() is sometimes written as a conditional probability distribution P(y|x).

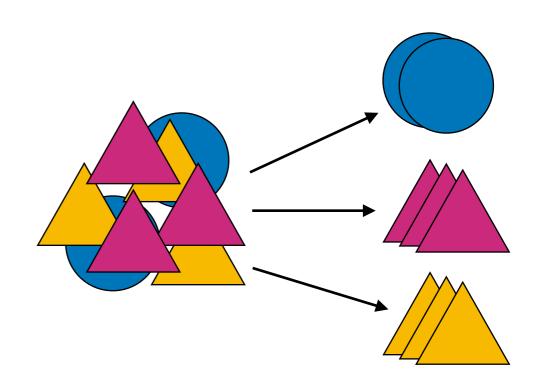
Definition 3. Given a set of source domains $D_S = D_{s_1}$, ..., D_{s_n} where n > 0, a target domain, D_T , a set of source tasks $T_S = T_{s_1}$, ..., T_{s_n} where $T_{s_i} \in T_S$ corresponds with $D_{s_i} \in D_S$, and a target task T_T which corresponds to D_T , transfer learning helps improve the learning of the target predictive function $f_T()$ in D_T where $D_T \neq D_S$ and $T_T \neq T_S$.



Transfer Learning (cont.)

Transfer learning can be very useful in these areas:

- text classification (text clustering),
- reinforcement learning,
- sentiment classification,
- collaborative filtering,
- sensor-based location estimation,
- Al planning,
- metric learning.

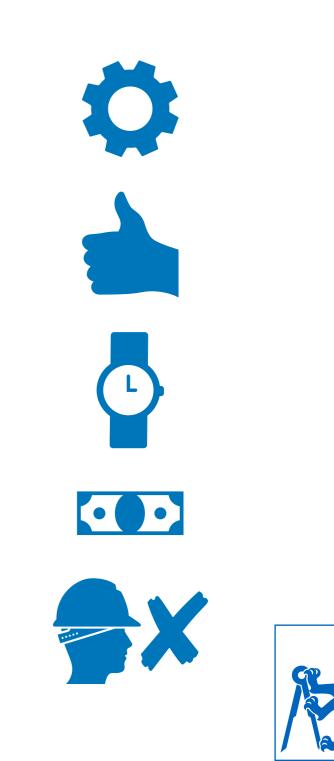




Transfer Learning (cont.)

Transfer learning offers benefits:

- automatization of mapping process,
- increasing usability of poor data,
- saving time,
- saving human resources,
- no presence of domain expert necessary.



Fields of Transfer Learning

1) Transfer Learning for reinforcement learning:

- Taylor, M. E. and Stone, P. (2009) - Transfer Learning for Reinforcement Learning Domains: A Survey.

2) Transfer learning for classification and regression problems:

- Pan, S. J. and Yang, Q. (2009) - A survey on transfer learning.

- Weiss, K., Khoshgoftaar, T. M., and Wang, D. D. (2016) - A survey of transfer learning.



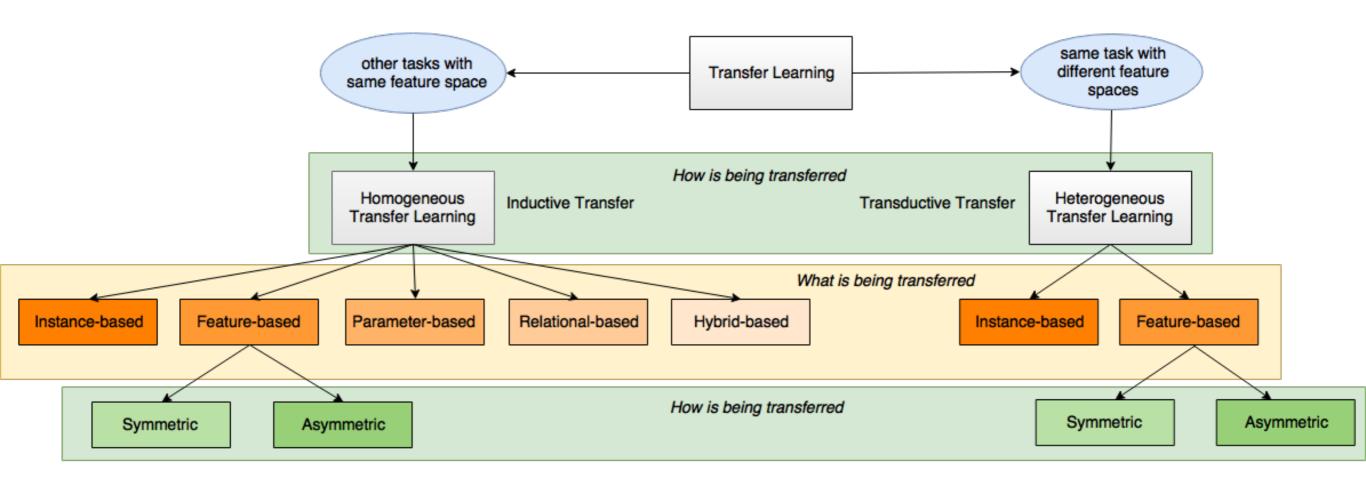
Research Issues

Three main research issues:

- What to transfer?
 - Asks which part of knowledge can be transferred.
- How to transfer?
 - Defines the algorithm that extracts the knowledge.
- When to transfer?
 - Defines in which situations knowledge should not be transferred (negative transfer learning).



TL Hierarchy





What to Transfer

There exists four standard approaches:

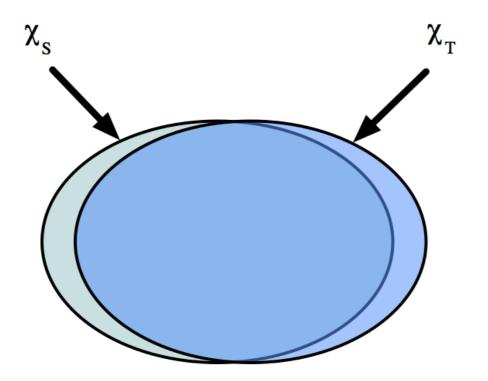
- instance-based transfer learning,
- feature-based transfer learning,
- parameter-based transfer learning,
- relational-based transfer learning.



Instance-based TL

The main assumption:

• Source and target domains have a lot of overlapping features.

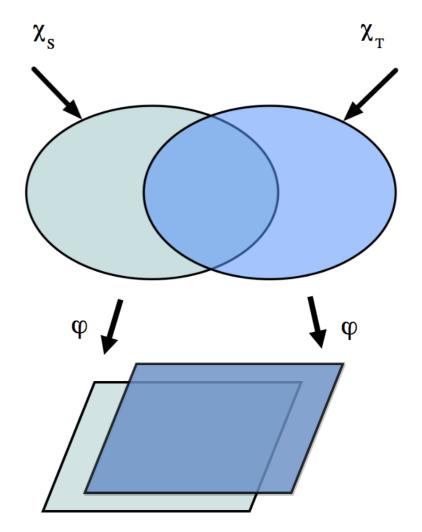




Feature-based TL

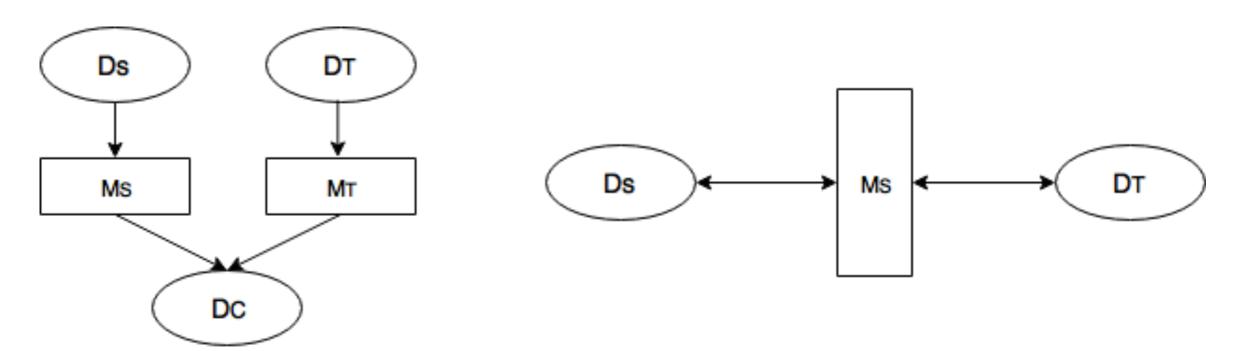
The main assumption:

 Source and target domains only have some overlapping features.





How to Transfer



Symmetric Approach

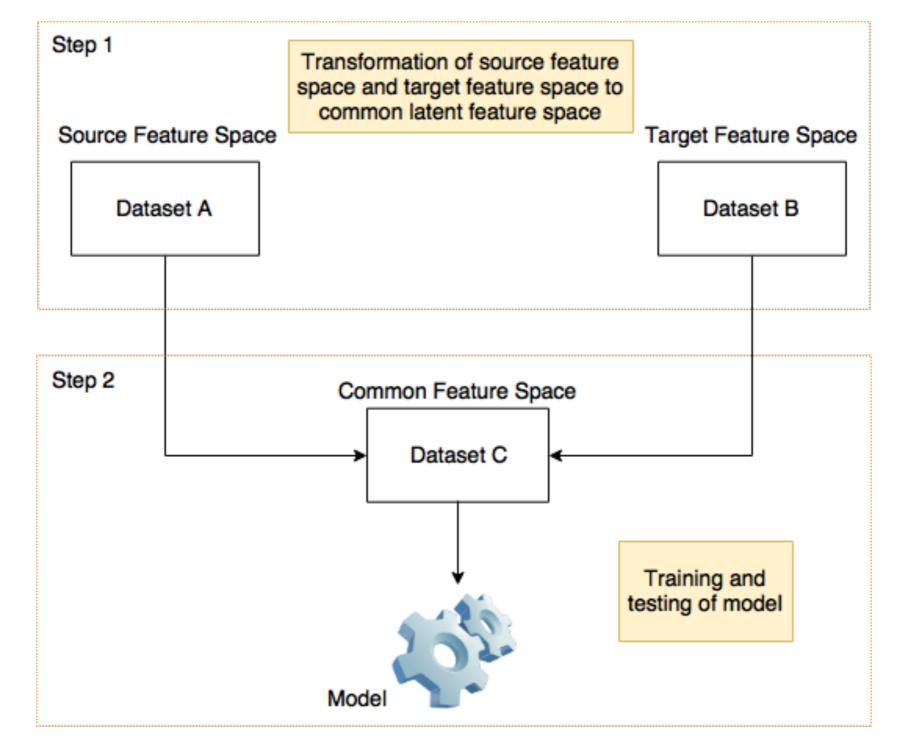
- Source domain D_S
- Target domain D_T
- Specific transformation *M* for each domain (*M_S* and *M_T*)
- Latent space D_C

Asymmetric Approach

- Source domain D_S
- Target domain D_T
- Common transformation M

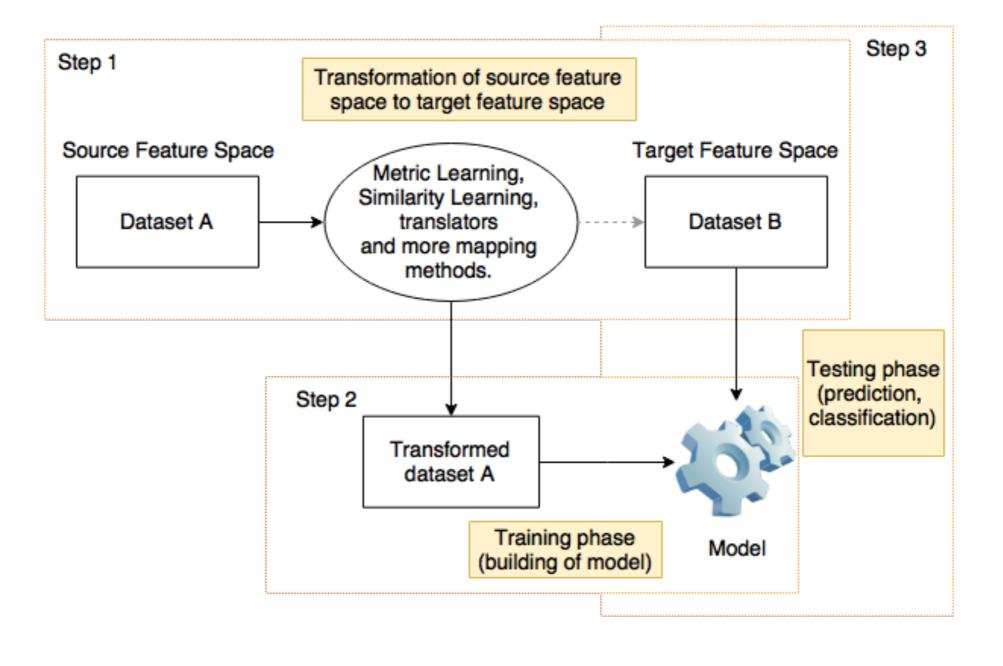


Symmetric Approach



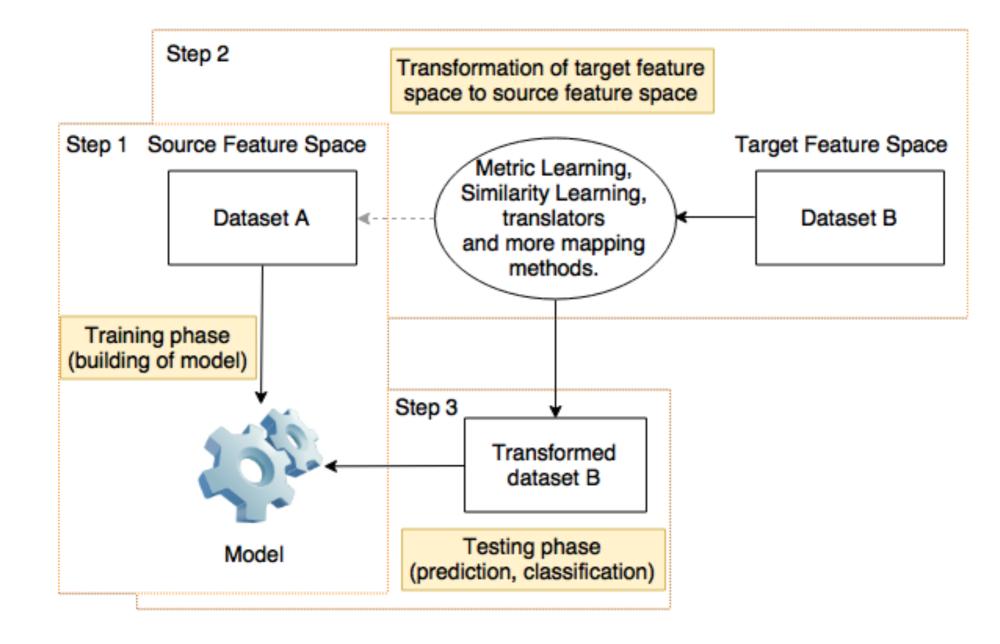


Asymmetric Approach no. 1





Asymmetric Approach no. 2





When to Transfer

Negative Transfer Learning:

- Transfer learning methods assume that the source and target domains are related to each other in some way. If this assumption does not hold, negative transfer may happen.
- We need to first study transferability between source domains or tasks and target domains or tasks and then select relevant source domains or tasks to extract knowledge.
- Fertile area for further research.



Another Settings

- 1. Inductive TL
 - the target task is different from the source task
 - labeled data in the target domain are required
- 2. Transductive TL
 - the target domain is different from the source domains
 - no labeled data in the target domain
- 3. Unsupervised TL
 - focused on unsupervised learning tasks in the target domain
 - no labeled data in both source and target domains



TL Challenges

- Negative transfer learning.
 - How to avoid negative transfer?
 - Robust negative transfer measurements.
- Another area of future work pertains to the scenario where the output label space is different between domains.
- Very few transfer learning solutions addressing the scenario of unlabeled source and unlabeled target data.
- Improved methods for correcting the conditional distribution differences.
- A lack of general solutions (mainly domain specific solutions) (mainly in heterogeneous field).
- How the diversity and large size of sensor data integrates into transfer learning solutions.
- Active learning.
- Cold-start problem.



My Research Area

Asymmetric Heterogeneous Transfer Learning

(e.g. same task, different domains, asymmetric approach)

We face to these problems:

- different feature representations,
- different numbers of features,
- different meanings of features,
- a few or no overlapping features.

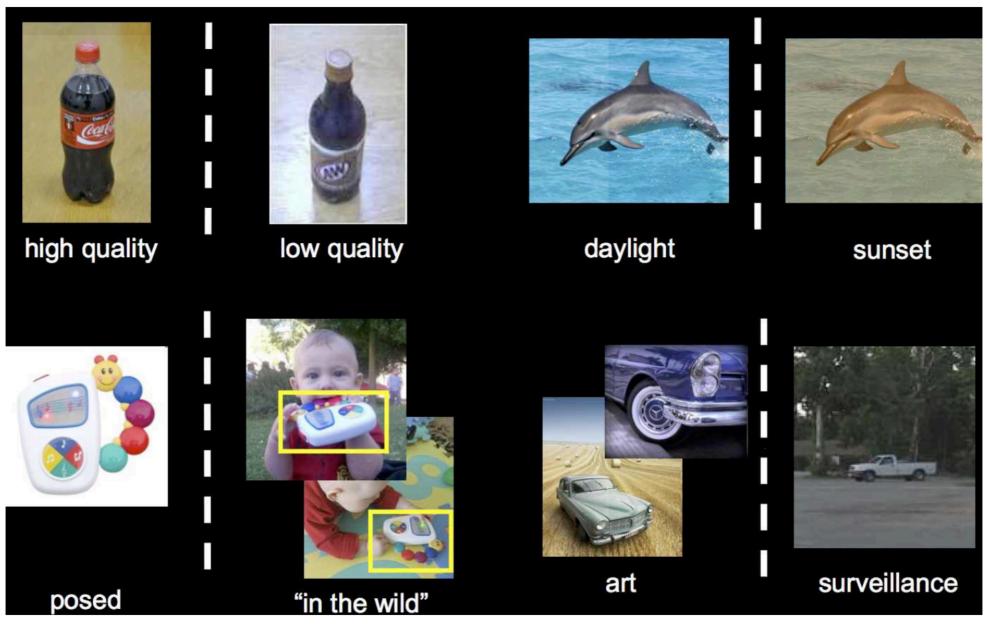


Definition of HetTL

Definition 4. Given a set of source domains $D_S = D_{s_1}$, ..., D_{s_n} where n > 0, a target domain, D_T , a set of source tasks $T_S = T_{s_1}$, ..., T_{s_n} where $T_{s_i} \in T_S$ corresponds with $D_{s_i} \in D_S$, and a target task T_T which corresponds to D_T , transfer learning helps improve the learning of the target predictive function $f_T()$ in D_T where $\chi_T \cap (\chi_{s_1} \bigcup ... \chi_{s_n}) = \emptyset$.



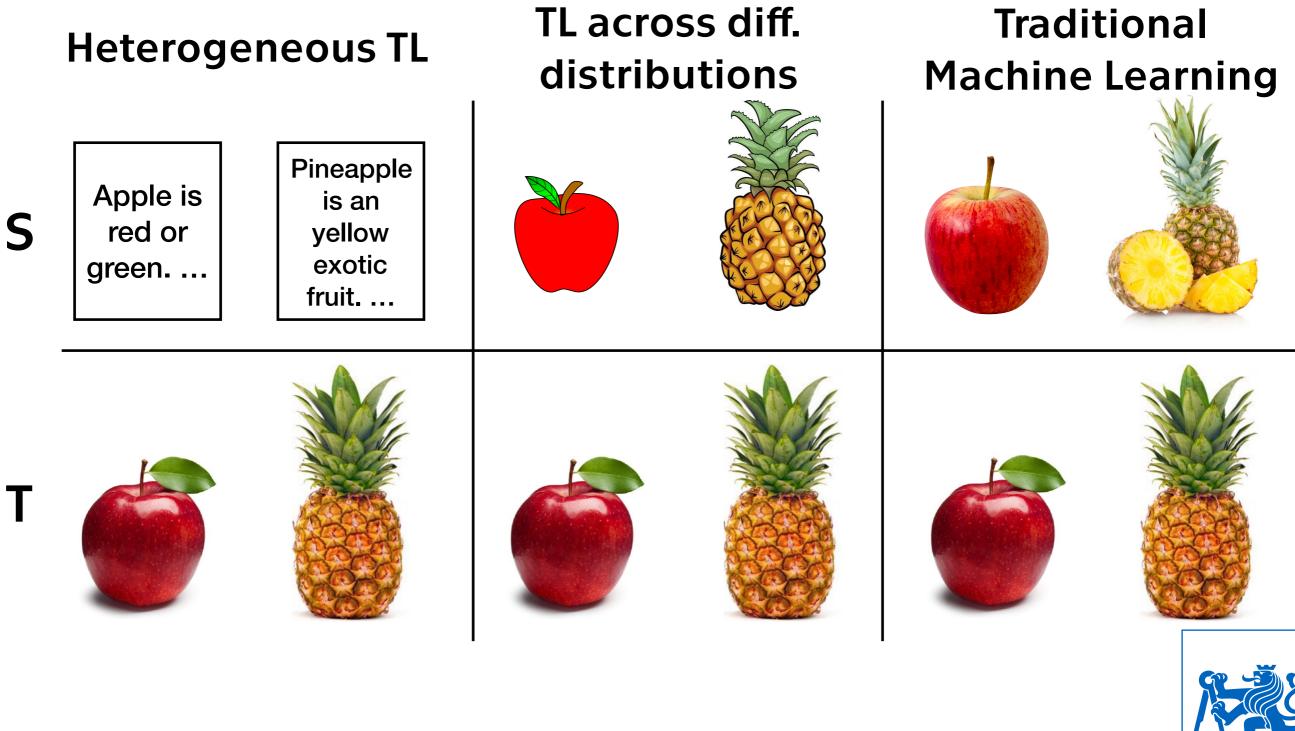
Problems with Data Representation







Problems with Feature Representation



Fields of Application

- **Computer vision image classification,**
- cross-language classification,
- cross-project defect prediction,
- activity recognition.







digital SLR camera

low-cost camera, flash



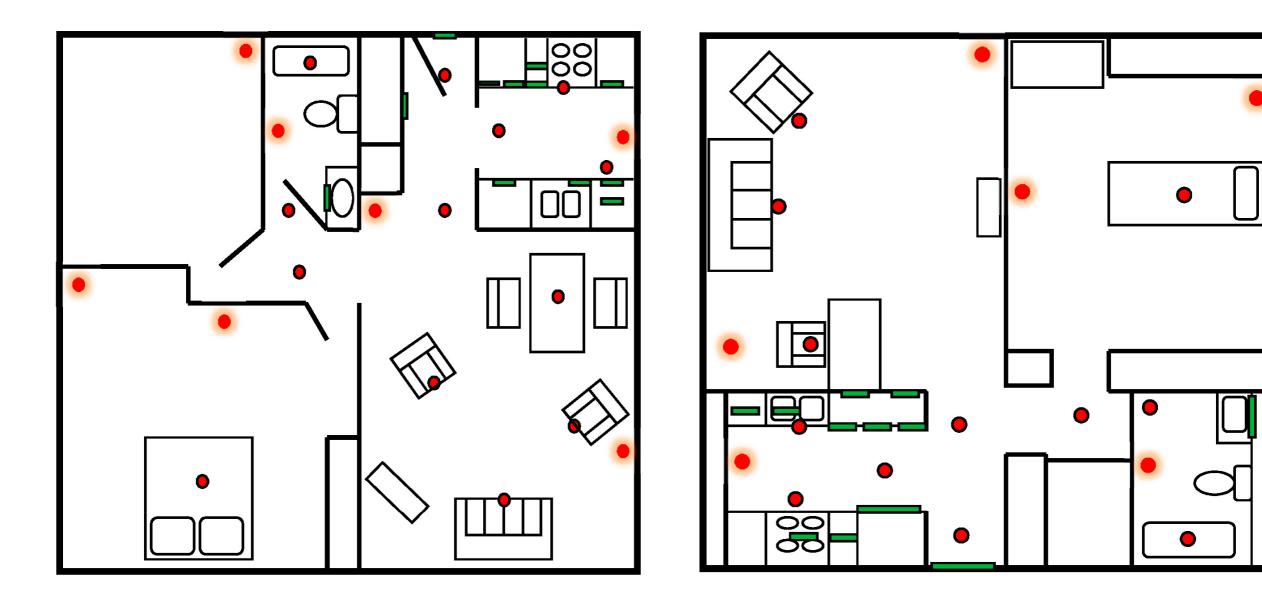
amazon.com

consumer images

[Kulis, B., Saenko, K., and Darrell, T. (2011)]



Activity Recognition Task



(a)

[Dahmen et al. (2017)]

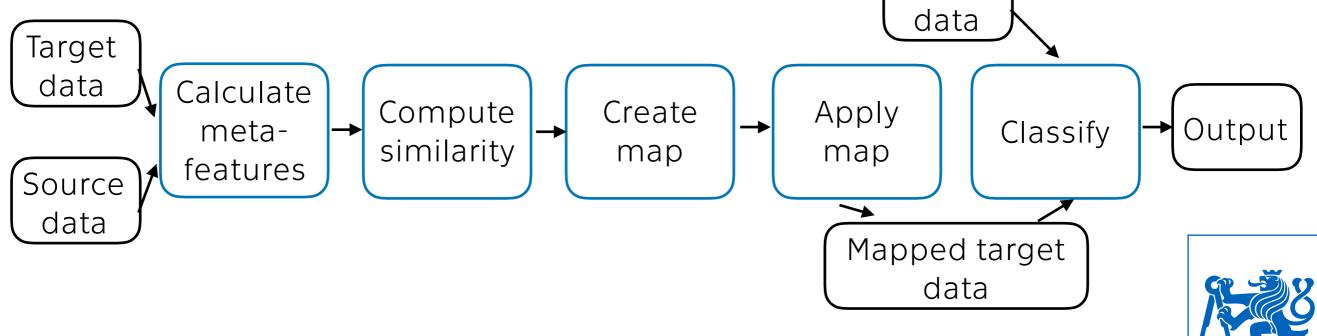
(b)



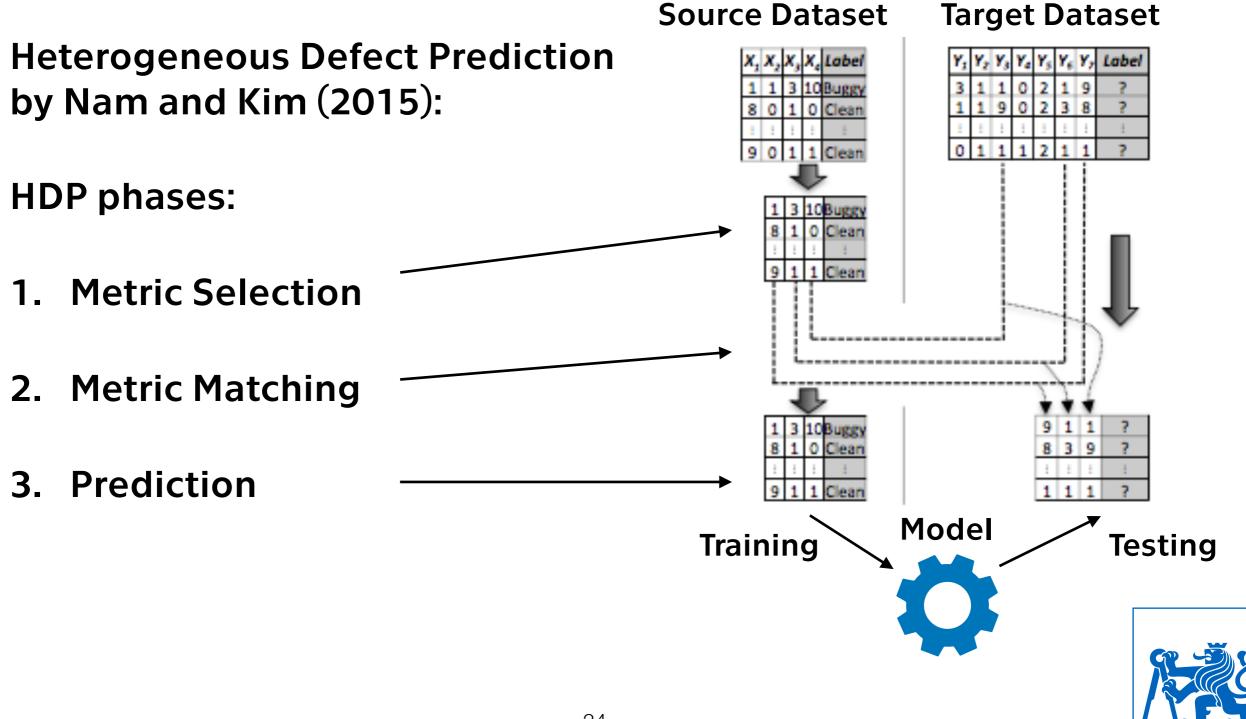
Activity Recognition Task (cont.)

Feature-Space Remapping method (Feuz and Cook, 2015):

- Requires a one time manual specification of meta-features.
- Computes the average similarity between the source and target meta-features.
- The similarity is the absolute value of the difference divided by the maximum possible difference.

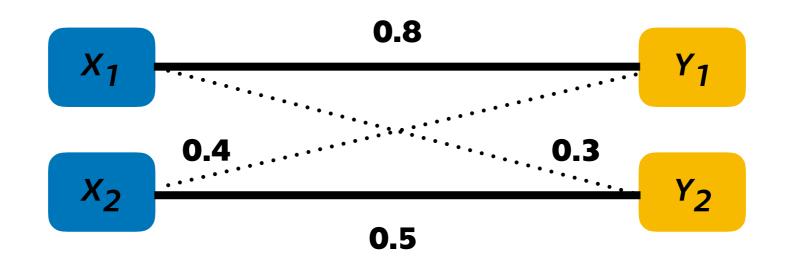


Cross-Project Defect Prediction



Cross-Project Defect Prediction- HDP (cont.)

- Used methods for measuring the source and target data similarity:
 - percentiles,
 - Kolmogorov-Smirnov Test,
 - Spearman's correlation.





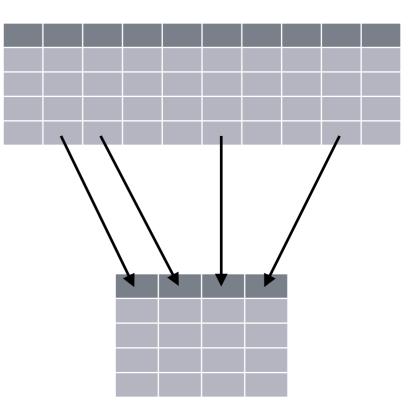
Feature Mapping

State-of-art of feature mapping:

- preprocessing,
- dimensionality reduction,
- feature selection.

Mappings used within transfer learning:

- statistic methods,
- metric methods.





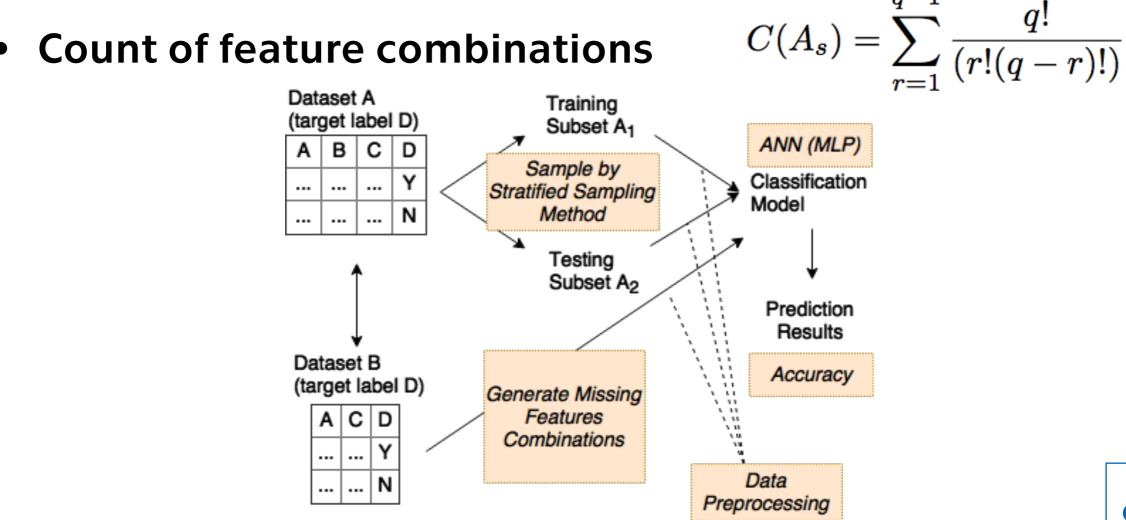
Actual Work

- Can we use a dataset with a few missing features for classification while preserving model accuracy? If we use such a dataset, how will the model perform?
- Is it possible to define a subset of features which are crucial for model accuracy? Can this subset be replaced by a subset of other features?
- Does a method which would determine whether a damaged dataset is usable for model classification without loss of model accuracy exist?



Actual Work (cont.)

 Definition of feature importance and its influence on model performance → Missing Feature Combination method (MFC).





Actual Work (cont.)

• MFC method output:

	0	1	2	3	4	5	6	7	8	9	10	11	12
10	0,71	1,00	0,48	1,00	1,00	1,00	0,71	0,71	0,71	0,81	1,00	1,00	0,90
15	0,50	1,00	0,25	1,00	1,00	1,00	0,00	0,75	0,75	0,00	1,00	1,00	1,00
20	0,88	0,50	0,56	1,00	1,00	1,00	0,38	0,69	0,31	0,50	1,00	1,00	1,00
25	0,68	0,50	0,45	1,00	1,00	1,00	0,36	0,32	0,55	0,27	1,00	1,00	0,82
30	0,41	0,38	0,48	1,00	0,86	1,00	0,17	0,21	0,66	0,45	1,00	1,00	1,00
35	0,89	0,28	0,56	1,00	0,83	1,00	0,39	0,39	0,28	0,28	1,00	1,00	0,56
40	0,46	0,76	0,51	1,00	0,68	1,00	0,49	0,44	0,44	0,15	1,00	0,95	0,51
45	0,63	0,68	0,44	1,00	0,80	1,00	0,29	0,59	0,49	0,17	0,95	0,66	0,61
50	0,52	0,63	0,46	1,00	0,62	0,89	0,23	0,34	0,40	0,23	0,97	0,82	0,57
55	0,58	0,55	0,53	1,00	0,71	0,71	0,19	0,57	0,44	0,13	0,96	0,66	0,58
60	0,53	0,57	0,43	0,97	0,58	0,66	0,22	0,56	0,40	0,30	0,93	0,75	0,54
65	0,49	0,55	0,50	0,90	0,53	0,67	0,21	0,50	0,45	0,25	0,89	0,70	0,57
70	0,53	0,54	0,48	0,86	0,55	0,56	0,25	0,56	0,48	0,29	0,86	0,61	0,60
75	0,54	0,54	0,49	0,72	0,57	0,60	0,35	0,55	0,46	0,34	0,79	0,60	0,62
80	0,50	0,51	0,49	0,61	0,48	0,50	0,33	0,52	0,42	0,38	0,65	0,50	0,57
85	0,48	0,48	0,51	0,35	0,47	0,44	0,62	0,48	0,53	0,60	0,34	0,44	0,44



Thank you!



References

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