



ICML
International Conference
On Machine Learning



山西大学
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Human Cognition-Inspired Hierarchical Fuzzy Learning Machine

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Outline



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1

Motivation

2

Method Design

3

Theory Analysis

4

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Conclusion and Outlook

2. Method Design

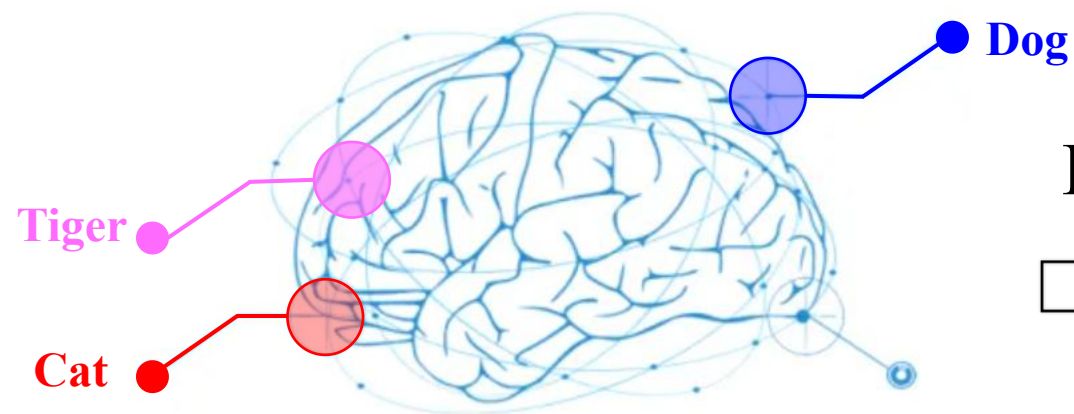


- **Classification is a cornerstone of machine learning**
- **A vast array of classifiers, categorized into**
 - **Based on discrete 0-1, such as KNN, Decision tree, Naive Bayes, etc.**
 - **Based on continuous proxies of 0-1 loss, such as Support Vector Machine (hinge loss), AdaBoost (exponential loss), Deep Neural Network (cross-entropy loss), etc.**
- **Underlying assumption, i.e., the concepts can be precisely defined**
- **However, in human cognition**
 - **concepts are often inherently ambiguous**
 - **concepts are deeply embedded in human knowledge system**

2. Method Design

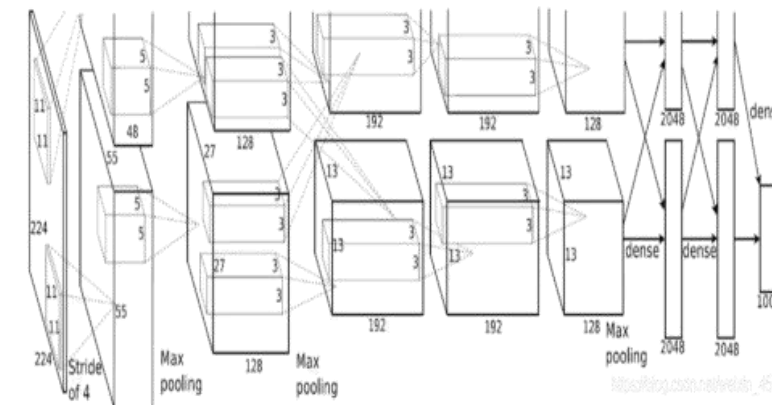
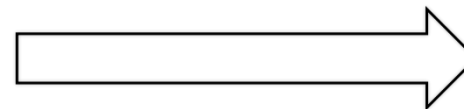


■ Overall Goal



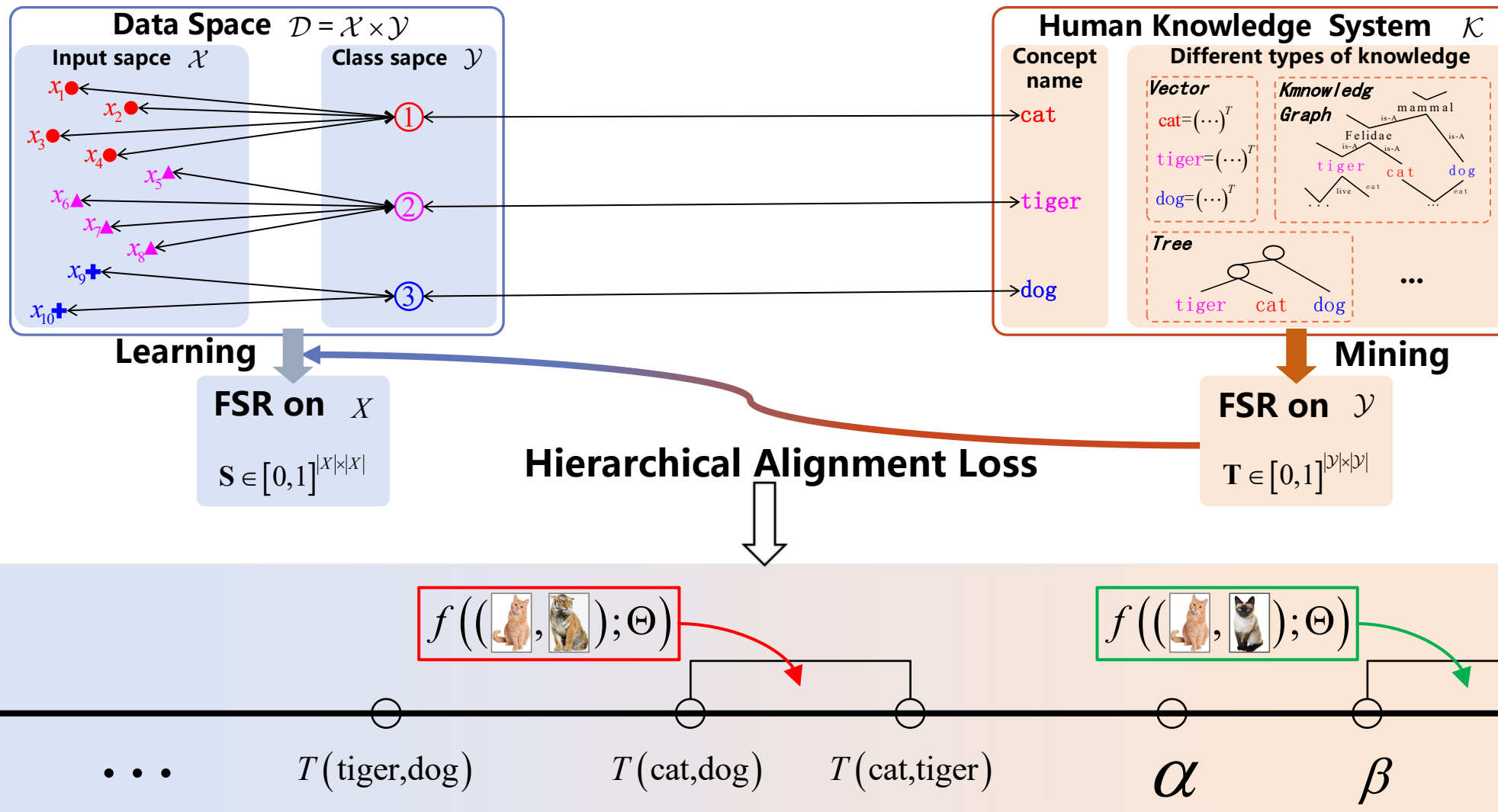
**Class Knowledge Contained in
Human Knowledge System**

Integrate into

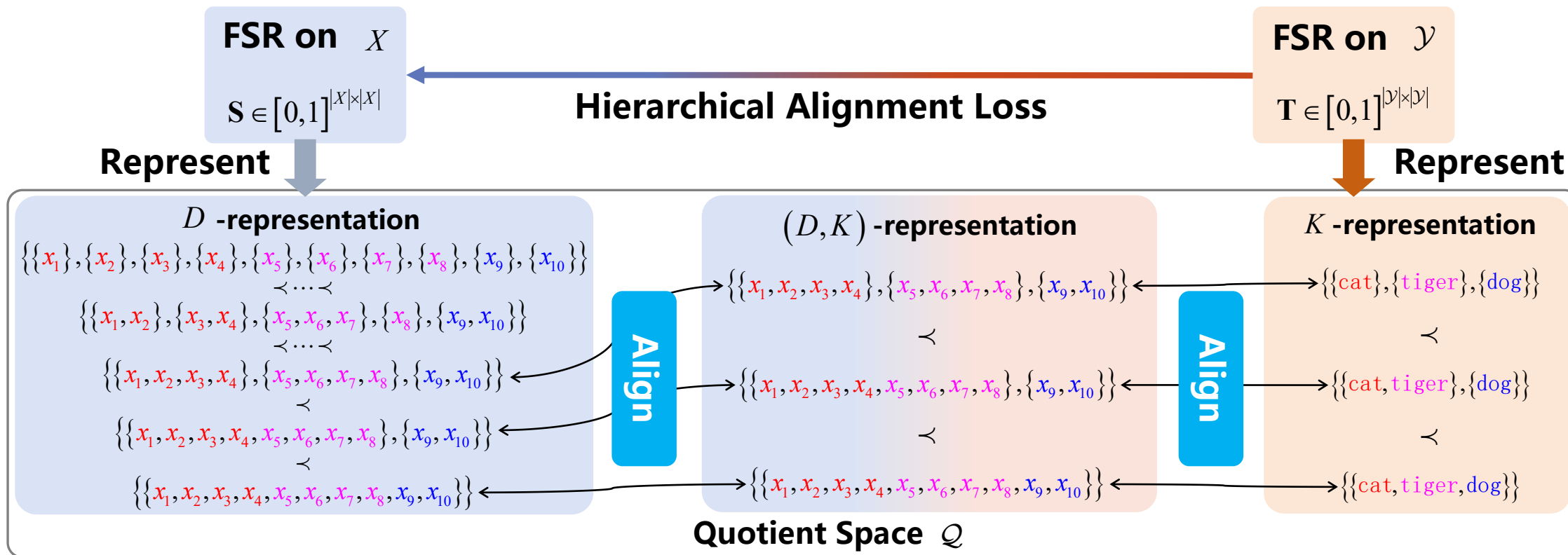


Machine Learning Model

2. Method Design



3. Theory Analysis



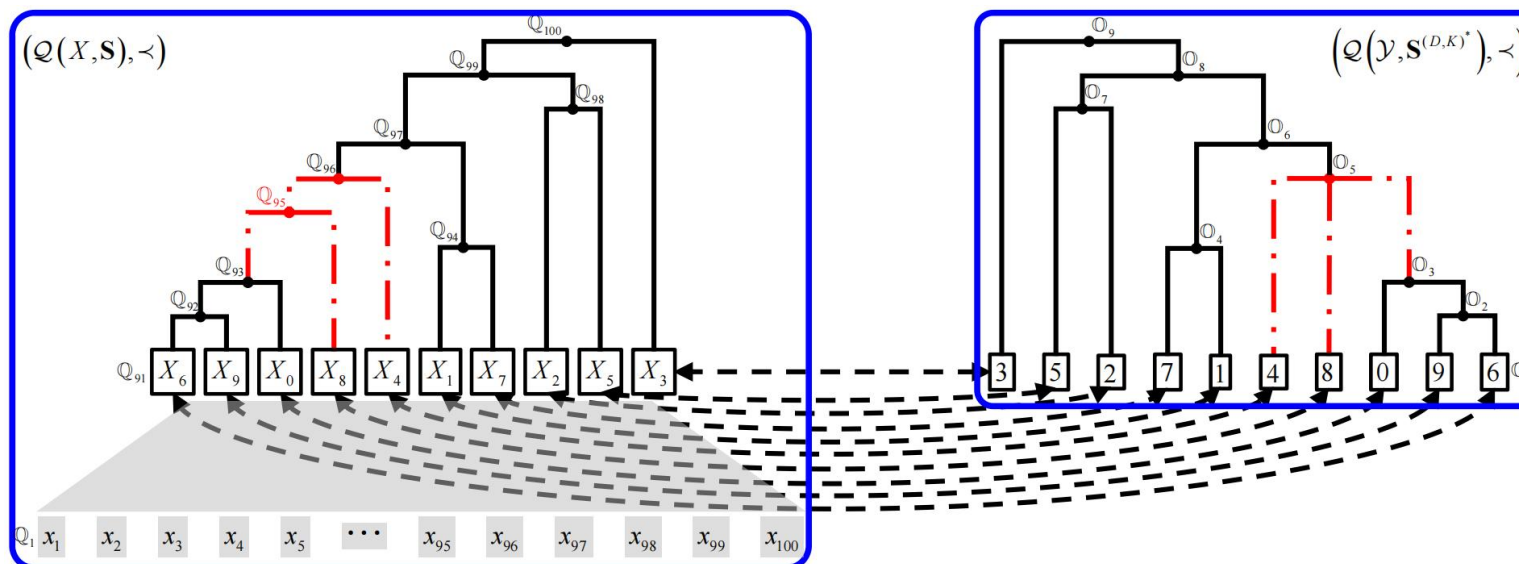
- ① Construct FSR-based Quotient Space Theory
- ② Represent Data and Knowledge in Quotient Space
- ③ Align Data and Knowledge in Quotient Space

4. Experiment



■ Interpretability Analysis

- MNIST data set, 100 training sample, 10 samples per class
- Class FSR, constructed by 10 human volunteers
- Result



The hierarchical structures derived by **Human Knowledge** and **Training Data** are aligned

4. Experiment



■ Generalization Analysis

- 6 data set, i.e., APY, ImageNet, AWA1, AWA2, FLO, CUB
- 2 types of knowledge, i.e., class description vector (CK_1) and WordNet (CK_2)
- Result

	APY	IMAGENET1K	AWA1	AWA2	FLO	CUB
KNN	85.35	75.49	86.61	89.83	83.39	47.30
DT	63.13	—	63.47	70.09	42.65	21.64
SVM	84.54	—	84.26	89.06	86.56	43.89
NB	76.13	73.66	84.67	87.68	85.53	60.27
CEC	89.08	75.62	88.48	91.67	93.58	61.49
FLM	89.42	76.02	89.95	92.79	<u>94.05</u>	<u>66.19</u>
CK_1-HFLM	90.23	<u>76.16</u>	91.10	93.59	95.06	68.78
CK_2-HFLM	<u>90.21</u>	76.20	<u>90.87</u>	<u>93.35</u>	N/A	N/A

Significant gains in **Generalization Performance**

5. Conclusion and Outlook



- Human knowledge are represented as class FSR
- By hierarchical alignment loss, class FSR guide the learning process
- Human knowledge and training data are aligned on quotient space
- Significant gains in interpretability and generalization performance
- Great promise for **open-world learning tasks, such as zero-shot learning and continual learning, etc.**

Thanks!



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