



# Advancements in Multi-label Learning

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# Introduction

## Multi-Label Learning:

- Predicting a **subset** of  $K$  **categories** (0 or 1 for each category)
- $f(\mathbf{x}) = \hat{\mathbf{y}}, \hat{\mathbf{y}} \in \{0, 1\}^K, 1 \leq \sum_{y \in \hat{\mathbf{y}}} y \leq K$

# Introduction (Contd.)

## Multi-Label Learning Caveats:

- ① Scalability to high-dimensional and large-scale datasets
- ② Handling label dependencies and interactions
- ③ Inconsistency between surrogate loss functions and evaluation metrics

# Advancements: Scalability

**Challenge:** Scalability to High-Dimensional and Large-Scale Datasets

**Advancements:**

- **Representation Learning:** Reduce data complexity. Focus on relevant information.
  - Demir, et. al., Co-operative Co-evolutionary Many-objective Embedded Multi-label Feature Selection with Decomposition-based PSO, ACM GECCO, 2023.
  - Hu, et. al., Dynamic subspace dual-graph regularized multi-label feature selection, Neurocomputing, 2022.
  - Jian, et. al., Multi-label informed feature selection, IJCAI, 2016.

# Advancements: Label Dependencies

**Challenge:** Handling Label Dependencies and Interactions (*the hot topic!*)

**Advancements:**

- **Graph-Based Models:** Represent labels as nodes and relationships as edges in a graph.
  - Demir, et. al., Dual Sparse Structured Subspaces and Graph Regularisation for Particle Swarm Optimisation-based Multi-label Feature Selection, IEEE CIM, (Accepted).
  - Yuan, et. al., Graph Attention Transformer Network for Multi-label Image Classification, ACM TOMM, 2023.
  - Hang, et. al., Collaborative Learning of Label Semantics and Deep Label-Specific Features for Multi-Label Classification, TPAMI, 2022.
  - Wang, et. al., Cross-Modality Attention with Semantic Graph Embedding for Multi-Label Classification, AAAI, 2020.
  - Wang, et. al., Multi-Label Classification with Label Graph Superimposing, AAAI, 2020.

# State-of-the-art Methods

## Benefits:

- Enhanced ability (and efficiency) to handle complex real-world scenarios.
- Improved prediction accuracy by adapting to varying label dependencies.

# Advancements: Consistency

## **Challenge:** Surrogate Loss vs. Evaluation Metrics

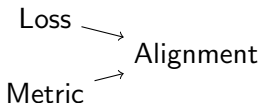
Many multi-label learning models optimize surrogate loss functions during training, which may not always align perfectly with the desired evaluation metrics (e.g., Hamming loss, Ranking loss).

## **Advancements:**

- Actually, we have proven that consistency cannot be achieved in many cases (in-fact, only partial consistency):
  - Gao and Zhou, On the consistency of multi-label learning, PMLR, 2011.
  - Liu, et. al., The Emerging Trends of Multi-Label Learning, TPAMI, 2022.

# What *is* "consistency" (and why should we care about it)?

Usually, the learning behaviour of model  $f$  is prescribed by the gradients (or direction) of a carefully designed loss function  $\psi$ .



$$\psi(p(\mathbf{x}), f) = \sum_{\mathbf{y} \in \mathcal{Y}} p(\mathbf{y}|\mathbf{x}) \psi(f(\mathbf{x}), \mathbf{y}) \quad (1)$$

$$R_\psi(f) = \mathbb{E}_{(\mathbf{x}, \mathbf{y}) \sim \mathcal{P}}[\psi(p(\mathbf{x}), f)] \quad R_\psi^B(f) = \mathbb{E}_{(\mathbf{x}, \mathbf{y}) \sim \mathcal{P}}[\inf_{f'}[\psi(p(\mathbf{x}), f')]] \quad (2)$$



# Multi-label Consistency

Suppose  $\psi$  is the surrogate loss approximating  $\mathcal{L}$ , then given some sequence  $f^{(n)}$  if:

$$\lim_{n \rightarrow \infty} R_{\psi}(f^{(n)}) \rightarrow R_{\psi}^B(f) \quad \text{then} \quad R_{\mathcal{L}}(f^{(n)}) \rightarrow R_{\mathcal{L}}^B(f) \quad (3)$$

$\exists f \in \Omega$ .

## Multi-label Consistency (Contd.)

**This is not the case for almost all multi-label metrics!**

Please refer to Gao and Zhou, On the consistency of multi-label learning, PMLR, 2011.

# Conclusion

Multi-label learning has seen significant advancements:

- Scalability enabling efficient processing of large datasets.
- Handling label dependencies and interactions.
- Consistency remains an open topic.

Further exploration and collaboration are crucial for progress in this field.



**Thank you** for your attention! Any questions?