# **AQ-S³VSVM**: **A**ctive **q**ueries on **semi-supervised V**irtual **S**upport **V**ector **M**achines for classification of EO data

## ESA Living Planet Symposium 2025

D.02.08 Explainable AI for Earth Observation and Earth Science - PART 1 – Hall G1, June 27th, session: 8:30-10 a.m., talk: 8:30-8:45 a.m.

**Christian Geiß**[*,1,2], **Lorenzo Carlassara**[2,3], **Ludovico Giorgio Aldo Biagi**[3], **Hannes Taubenböck**[1,4], and **Patrick Aravena Pelizari**[1]

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[3] Department of Civil and Environmental Engineering, Politecnico di Milano, Italy.

[4] University of Würzburg, Institute of Geography and Geology, Chair of Remote Sensing, Am Hubland, 97074 Würzburg, Germany

# Introduction – Support Vector Machines

- 1963: Vapnik and Chervonenkis introduced the concept of the **maximum-margin hyperplane** for **linear** classification.

- 1990s: SVMs were further popularized and extended to handle **non-linear classification using the kernel trick** by Vapnik and collaborators (notably Corinna Cortes), especially in their 1995 paper "Support-Vector Networks".

vapnik

FOLGEN

Professor of Columbia, Fellow of NEC Labs America,
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machine learning   statistics   computer science

| TITEL | ZITIERT VON | JAHR |
|---|---|---|
| The Nature of Statistical Learning Theory<br>V Vapnik<br>Data mining and knowledge discovery | 110801 * | 1995 |
| Support-vector networks<br>C Cortes, V Vapnik<br>Machine learning 20, 273-297 | 75571 | 1995 |
| Backpropagation applied to handwritten zip code recognition<br>Y LeCun, B Boser, JS Denker, D Henderson, RE Howard, W Hubbard, ...<br>Neural computation 1 (4), 541-551 | 18989 | 1989 |
| A training algorithm for optimal margin classifiers<br>BE Boser, IM Guyon, VN Vapnik<br>Proceedings of the fifth annual workshop on Computational learning theory ... | 18689 | 1992 |
| Gene selection for cancer classification using support vector machines<br>I Guyon, J Weston, S Barnhill, V Vapnik<br>Machine learning 46, 389-422 | 12714 | 2002 |
| Support vector regression machines<br>H Drucker, CJ Burges, L Kaufman, A Smola, V Vapnik<br>Advances in neural information processing systems 9 | 7701 | 1996 |

Screenshot Google Scholar, June 23rd, 2025

# Objective – algorithm properties

1. **Maximum Margin Principle**

2. **Support Vectors**

# Objective

## Why in this session?

### D.02.08 Explainable AI for Earth Observation and Earth Science - PART 1

**Chair(s)**

Prof. Mihai Datcu (POLITEHNICA Bucharest), Nicolas Longepe (ESA)

**Room**
Hall G1

**Duration**
90 Minutes

efficiency

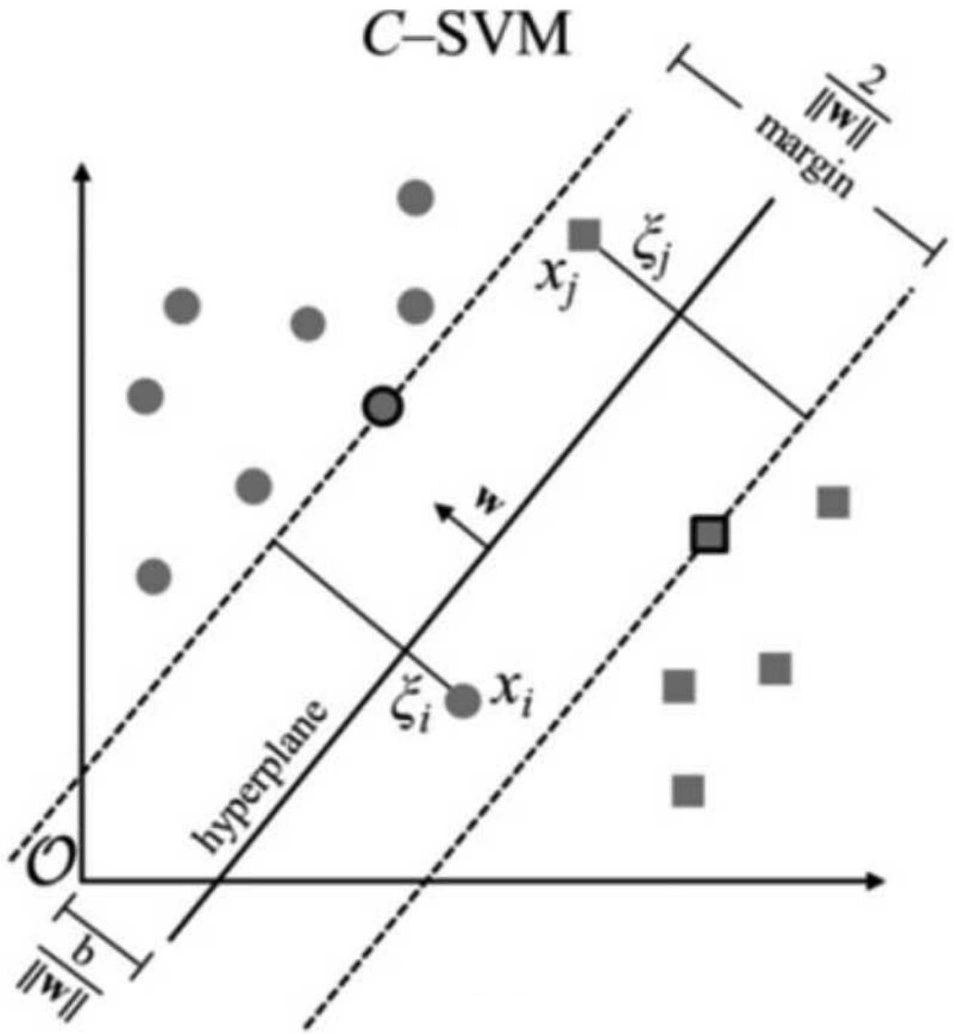
**Details**

The rapid expansion of AI in Earth system science and Earth observation (EO) is accelerating research and innovation. However, for AI-based solutions to be truly impactful in Earth Action initiatives, they must demonstrate explainability, physics-awareness, and trustworthiness to ensure they are fit for purpose.
This session will explore cutting-edge advancements in explainable AI (XAI) methods across diverse EO data types, including Synthetic Aperture Radar (SAR), optical, and hyperspectral data. Contributions are invited on integrating AI with physical models, interpretable deep learning, uncertainty quantification, causal inference, and other approaches to improve transparency, consistency, and robustness in AI-driven solutions.
We welcome case studies and research addressing a variety of Earth science missions and applications, such as SAR processing, Earth system process understanding, image classification, 3D reconstruction, and climate/environmental monitoring. The session will also cover strategies for tackling data gaps, physical inconsistencies, and ensuring responsible, ethical AI use.
Attendees will gain valuable insights into the latest research on explainable AI for EO, with a focus on enhancing model interpretability and trustworthiness in applications that advance Earth observation and Earth system science, supporting actionable solutions for environmental and climate challenges.

# The foundation: Support Vector Machines

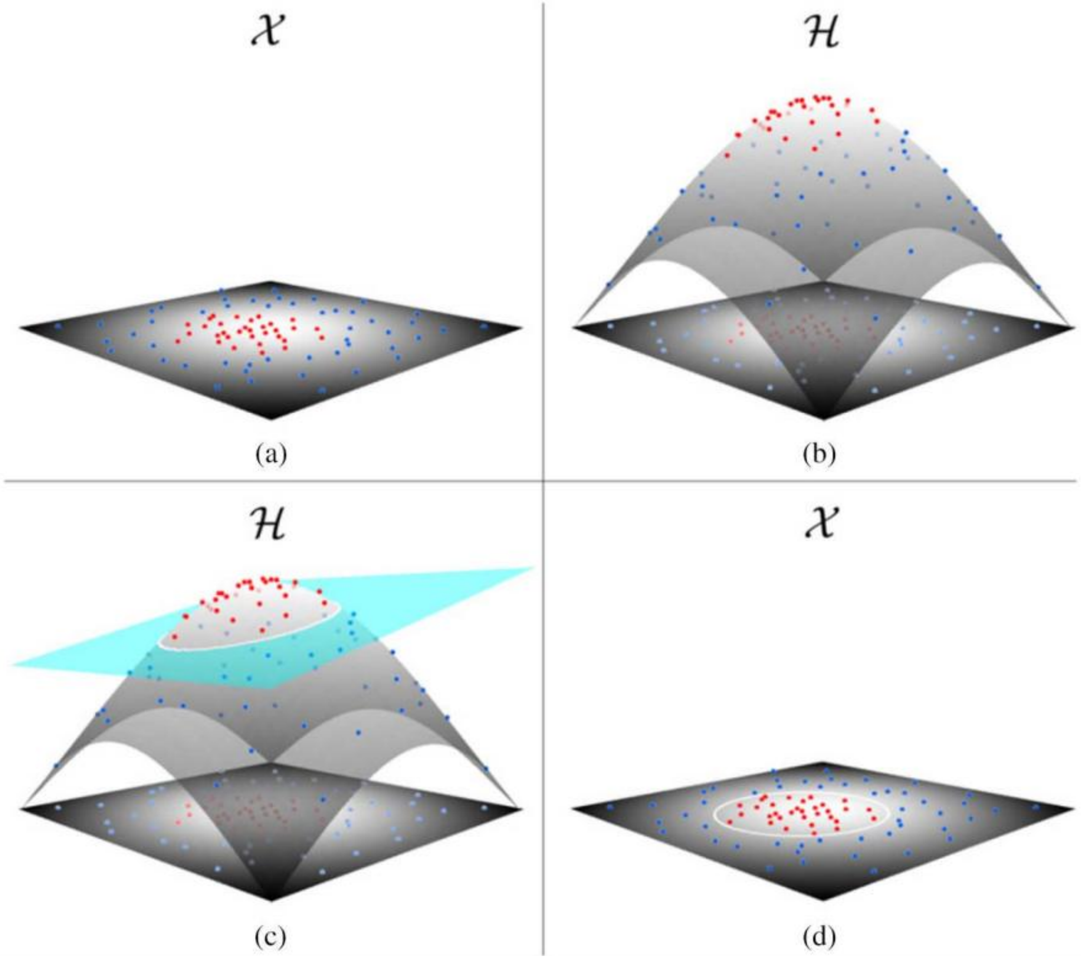
$$\min_{\mathbf{w},\xi_i,b}\left\{\frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i\right\}$$

minimization objective




feature space

# The foundation: Support Vector Machines – non-linear






Geiß, C., Jilge, M., Lakes, T., and Taubenböck, H. (2016): Estimation of Seismic Vulnerability Levels of Urban Structures With Multisensor Remote Sensing. *IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing*, 9, 5, 1913–1936.

# The foundation: Support Vector Machines

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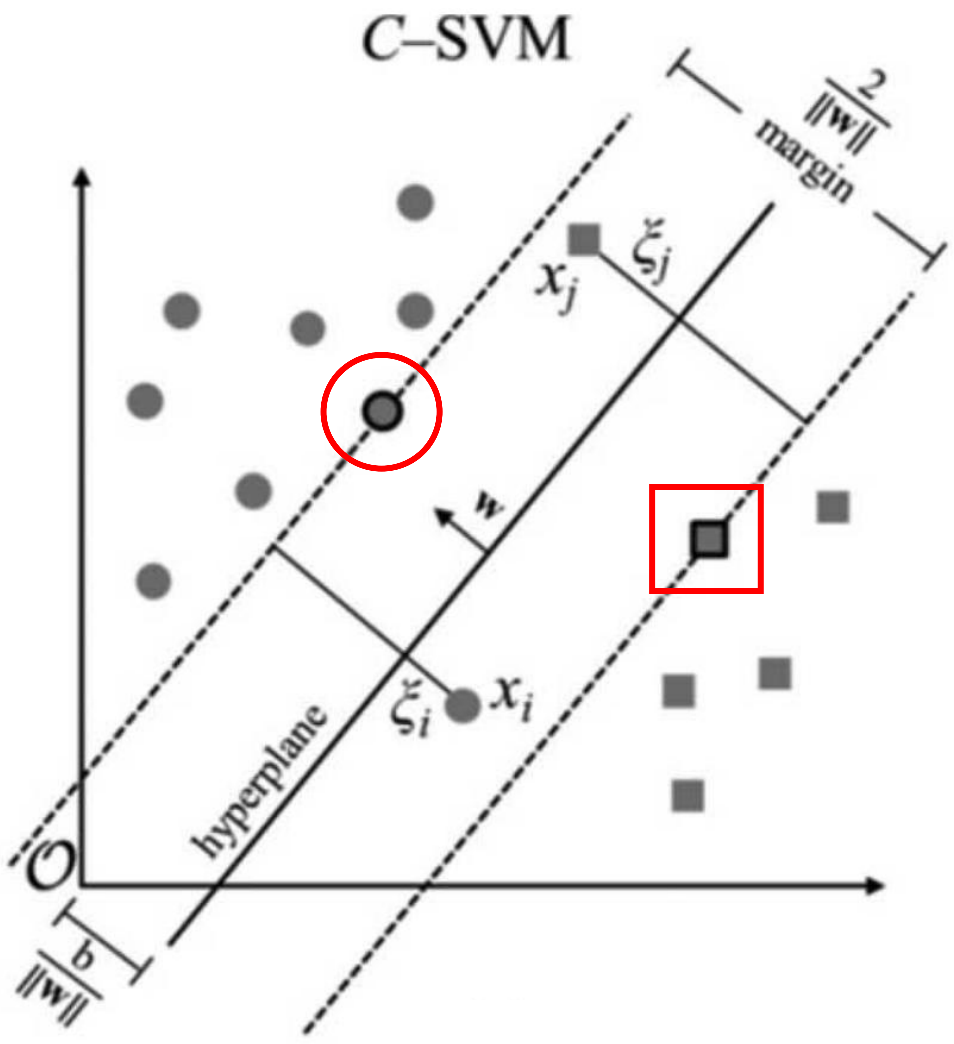
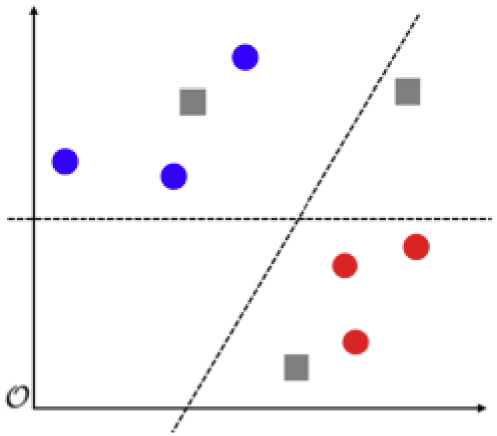



feature space

# Virtual Support Vector Machines, i.e., invariant SVMs

feature space

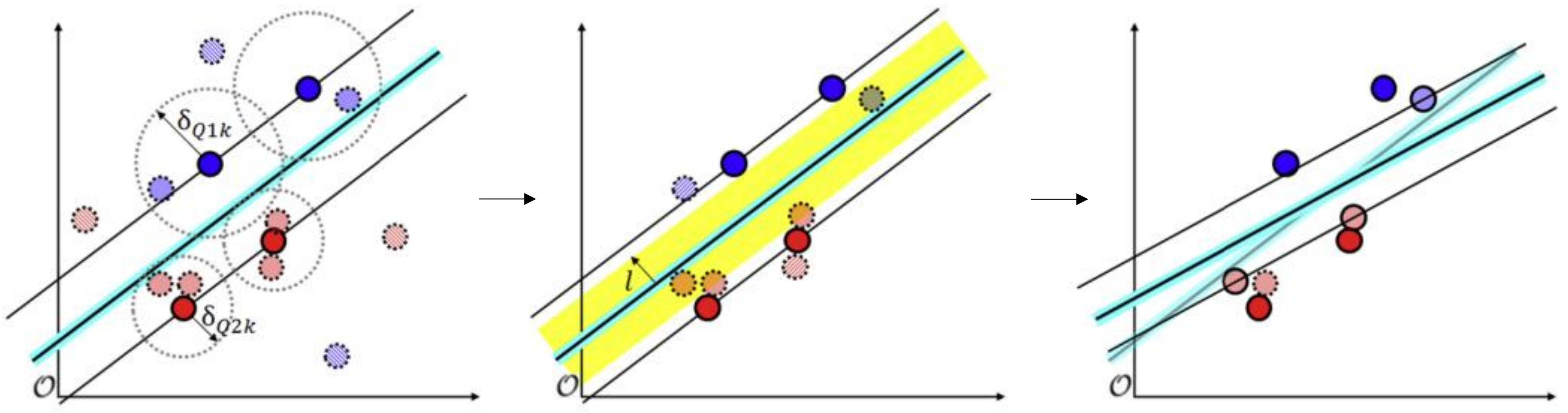
image space




Geiß, C., Aravena Pelizari, P., Blickensdörfer, L., and Taubenböck, H. (2019): Virtual Support Vector Machines with Self-Learning Strategy for Classification of Multispectral Remote Sensing Imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, 151, 42–58.

# constrained, i.e., robust, Virtual Support Vector Machines

eventually prune **virtual samples**




criteria 1: similarity constraint

criteria 2: margin constraint

final model

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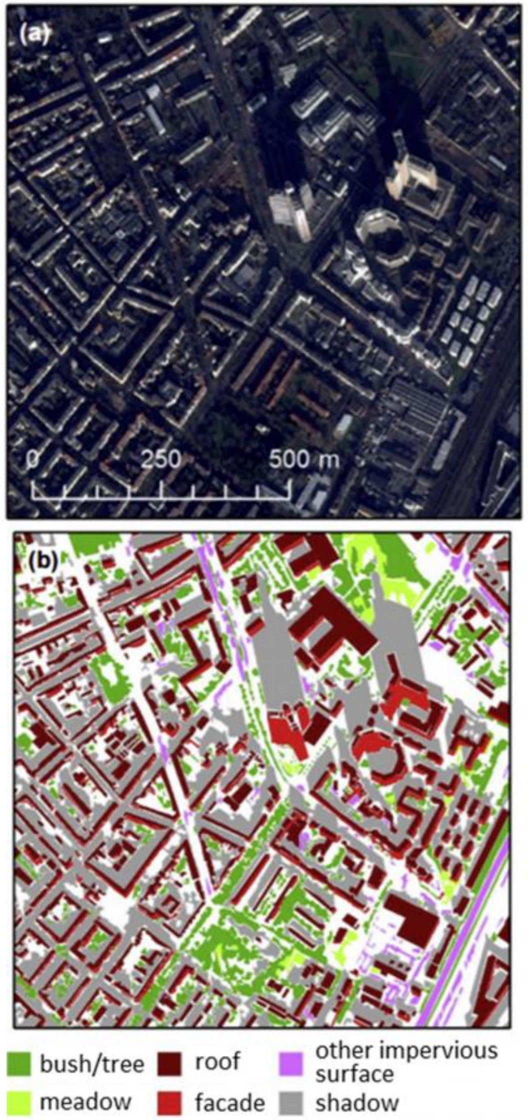
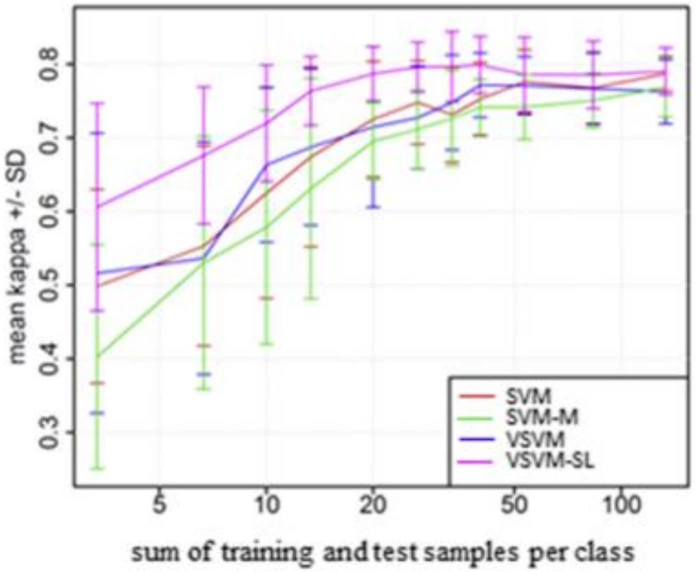
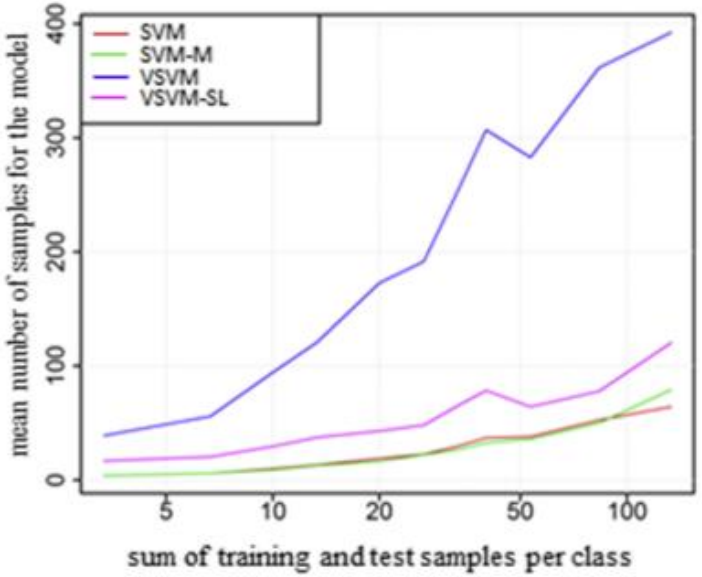
# experimental setup – multispectral imagery



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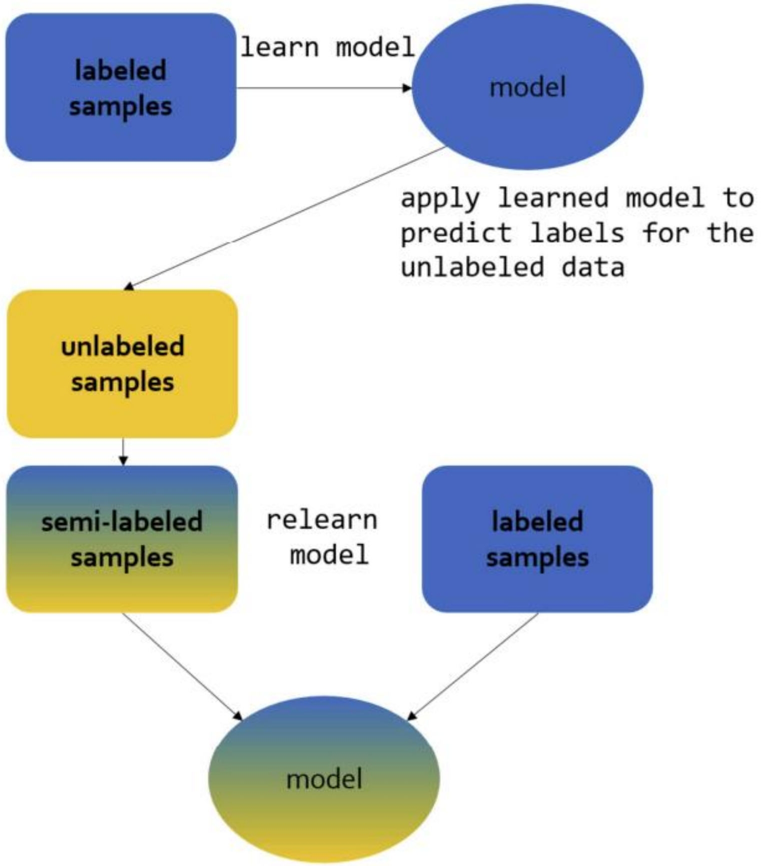
# semi-supervised Virtual Support Vector Machines

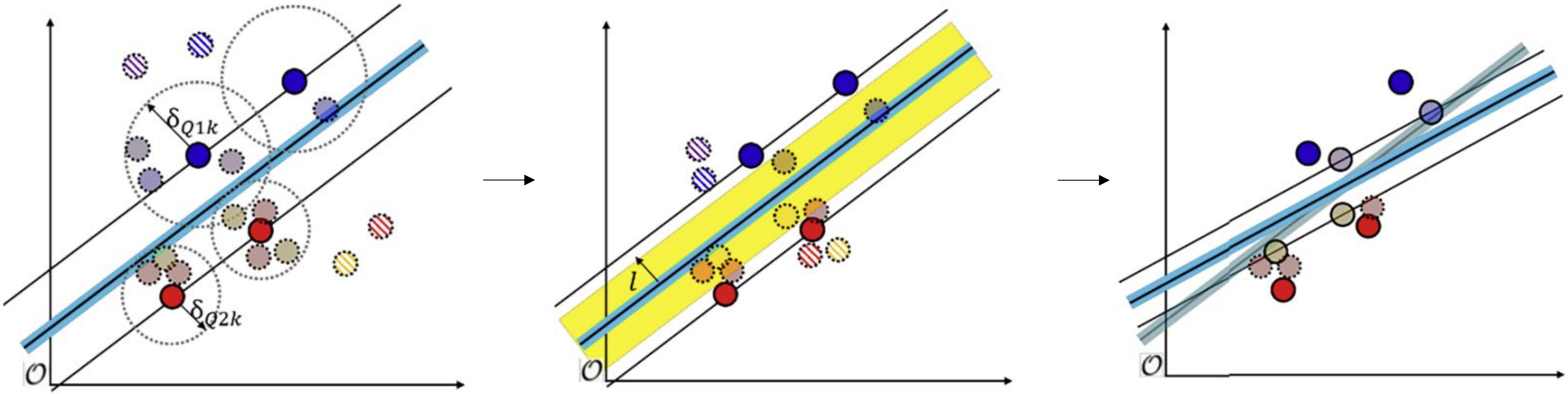
- Semi-supervised learning paradigm




*challenge*: how to <u>not</u> encode information that leads to <u>model divergence</u>?

# constrained, i.e., robust, Virtual Support Vector Machines

eventually prune **semi-labeled (virtual) samples**




criteria 1: similarity constraint

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final model



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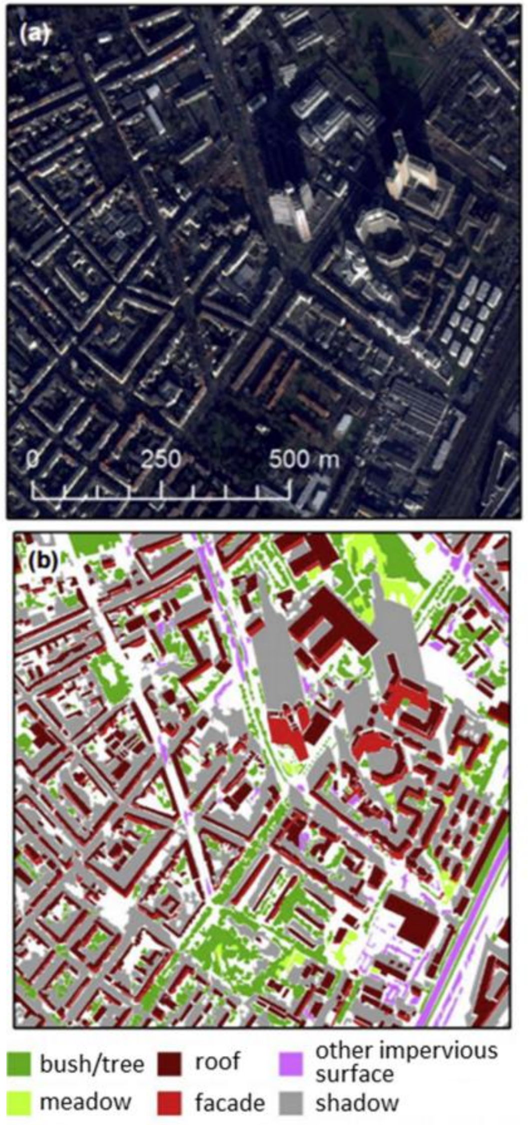
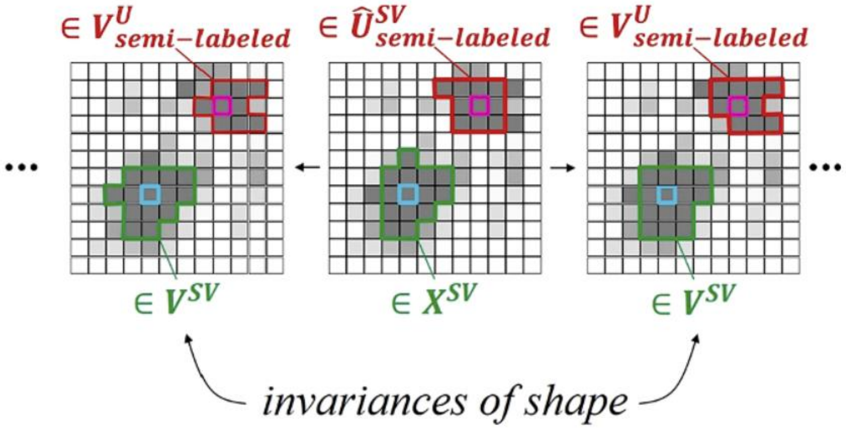
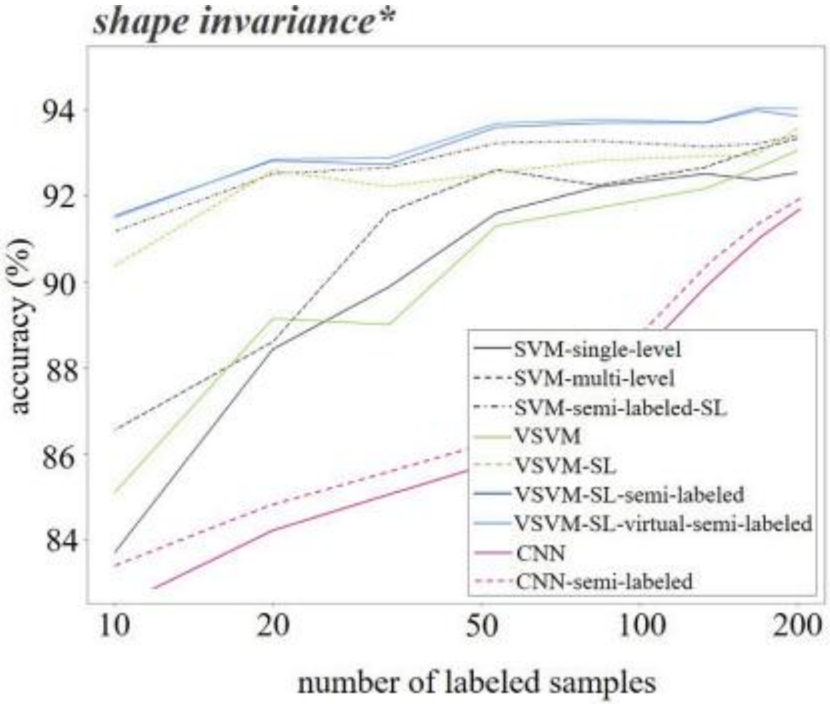
# semi-supervised Virtual Support Vector Machines



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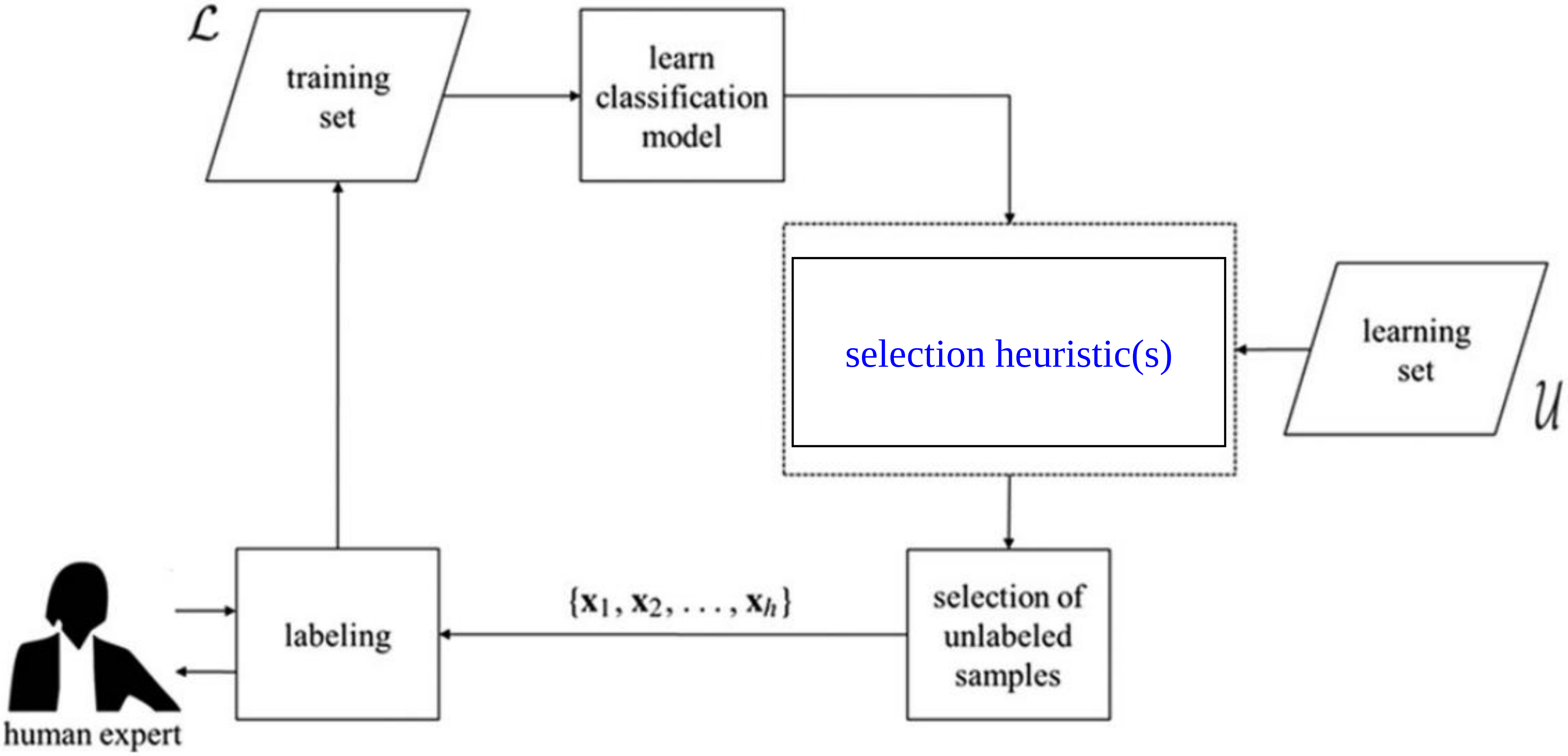
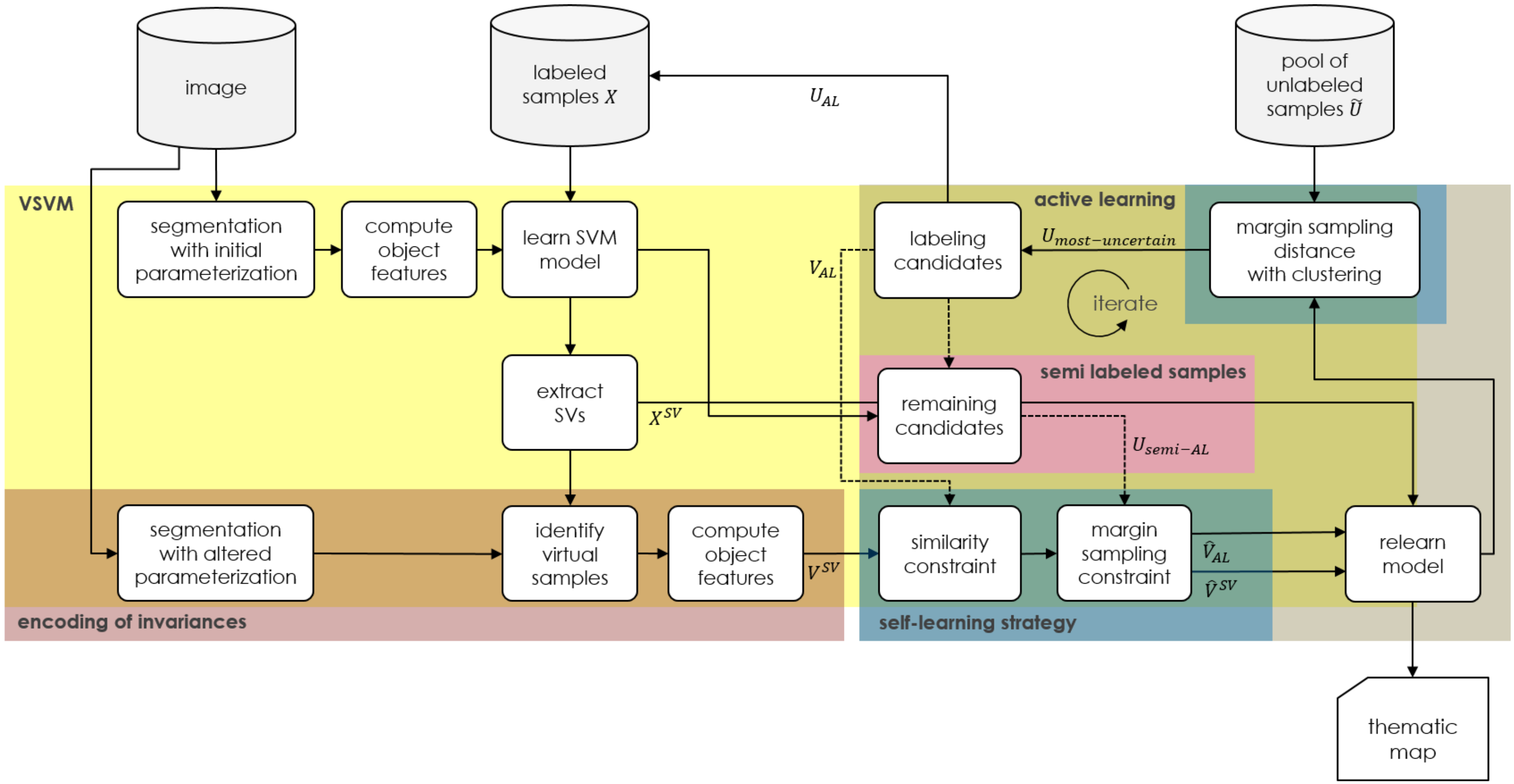
# AQ-S³VSVM: Active queries on semi-supervised Virtual Support Vector Machines for classification of EO data

- Active learning paradigm

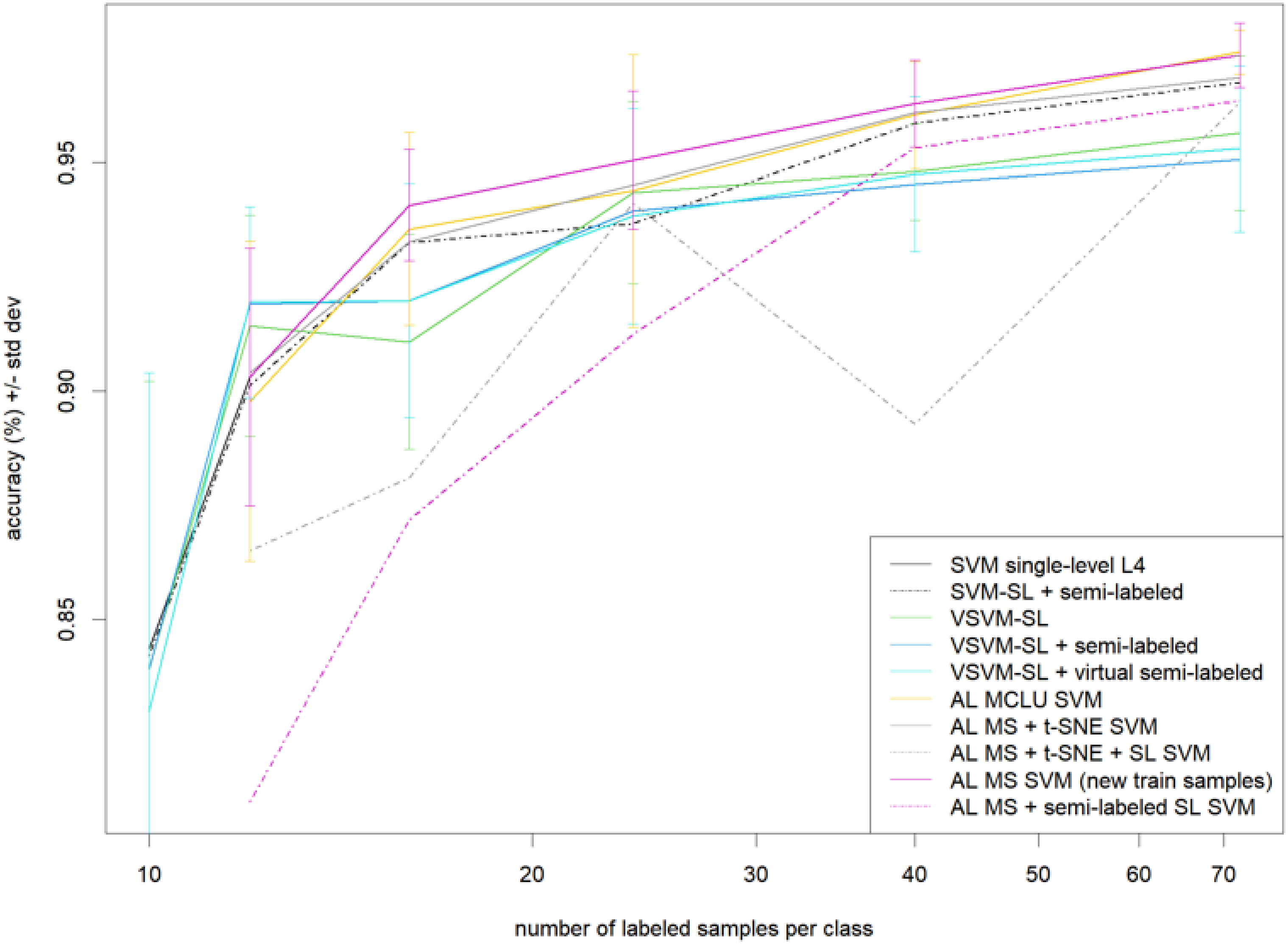


# AQ-S³VSVM: Active queries on semi-supervised Virtual Support Vector Machines for classification of EO data

- Active learning paradigm



# AQ-S³VSVM - preliminary results



# Conclusion and Outlook

- **efficient** framework for image classification with **little prior knowledge** (and no previously (unlabeled) encoded prior knowledge (e.g., foundation models))

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