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Towards the Development of a Global, Satellite-based, Terrestrial Snow Mission Planning Tool

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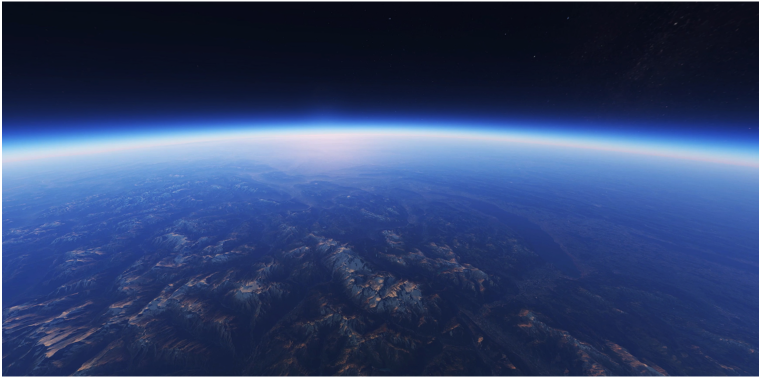
1=NASA GSFC - Hydrological Sciences; 2=NASA GSFC - Software Engineering; 3=Bay Area Environmental Research Institute

Bart Forman

Assistant Professor, University of Maryland
The Deborah J. Goodings Professor of Global Sustainability
Department of Civil and Environmental Engineering

December 12th, 2017

Satellite-derived Snow "Information"



Satellite-derived Snow "Information"

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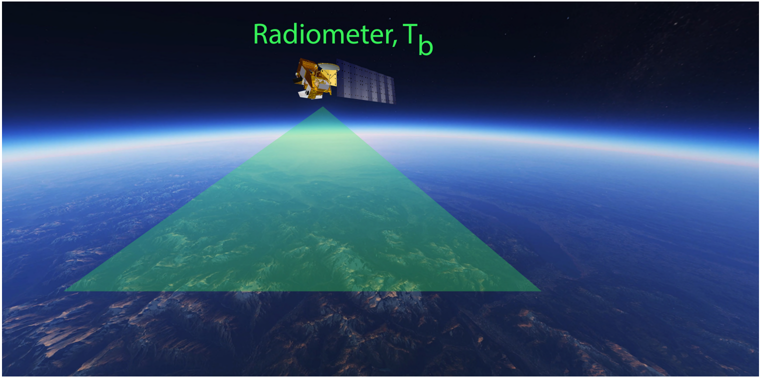

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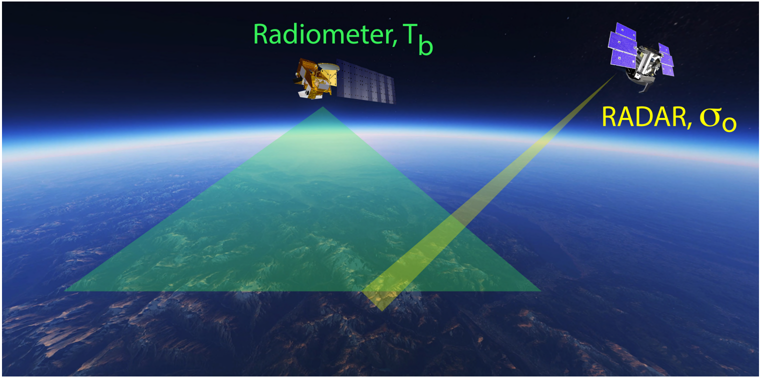

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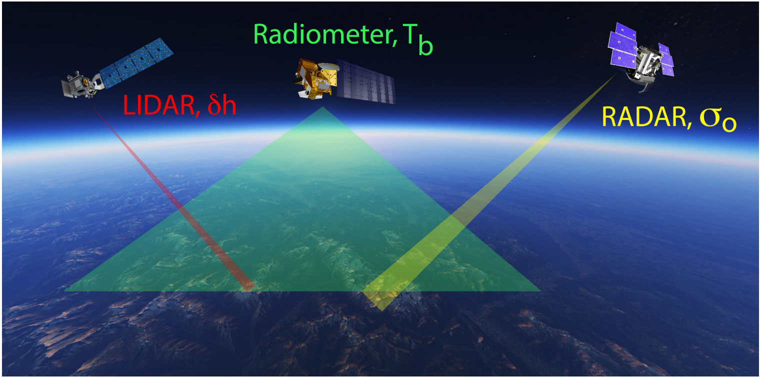

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Science and mission planning questions:

1. What observational records are needed (in space and time) to maximize terrestrial snow experimental utility?
2. How might observations be coordinated (in space and time) to maximize this utility?
3. What is the additional utility associated with an additional observation?
4. How can future mission costs be minimized while ensuring Science requirements are fulfilled?

Research Objectives

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Observing System Simulation Experiment

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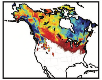
Nature Run

Snow Depth & SWE over North America



LIS + MERRA2
- model-based representation

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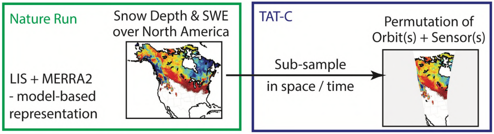

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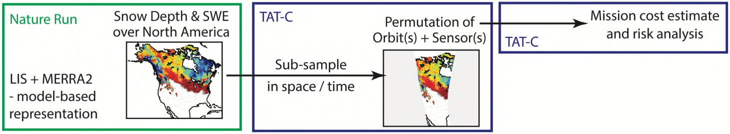

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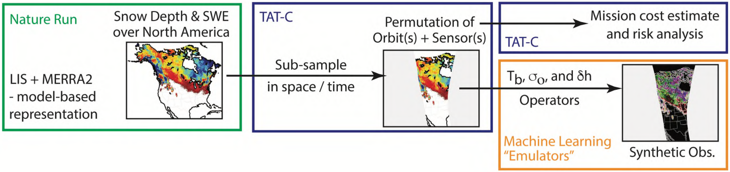

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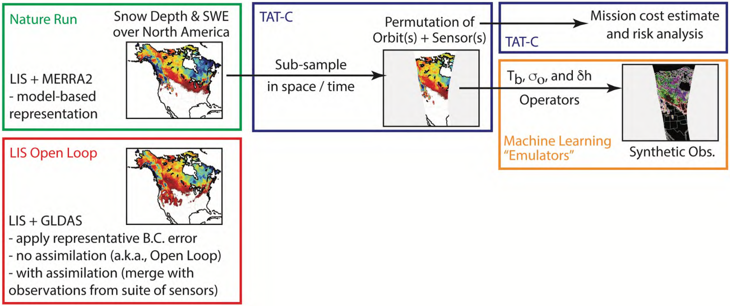

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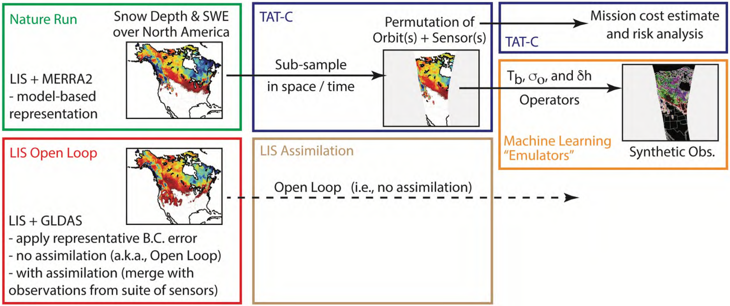

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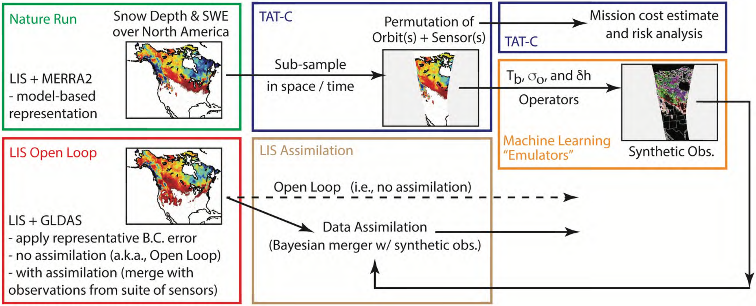

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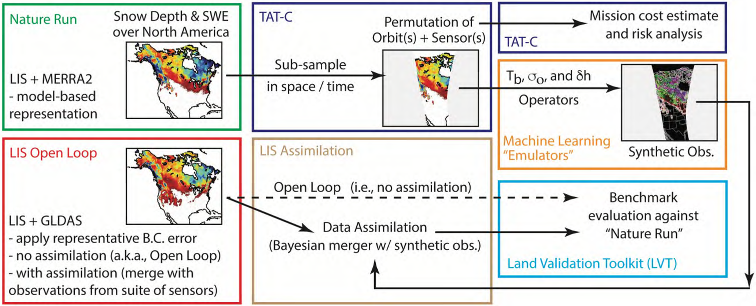
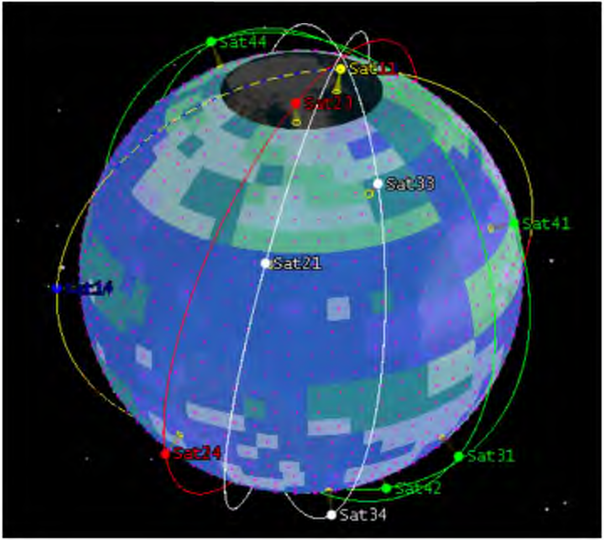


TAT-C Orbital Simulator



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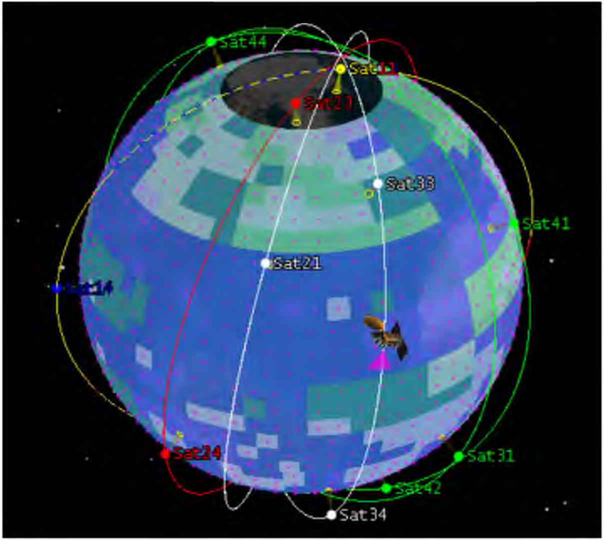

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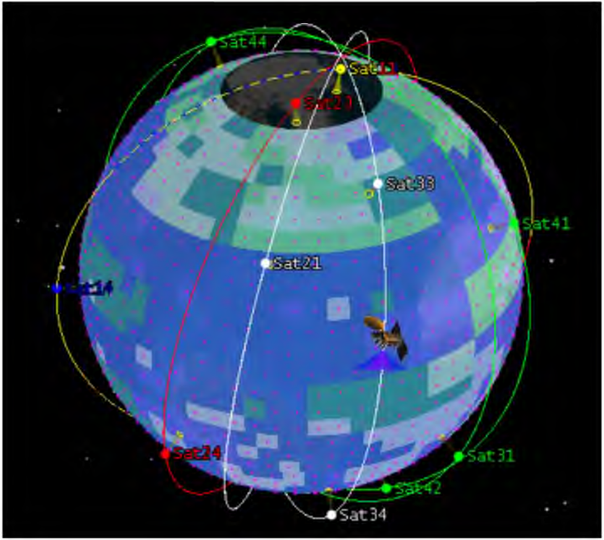

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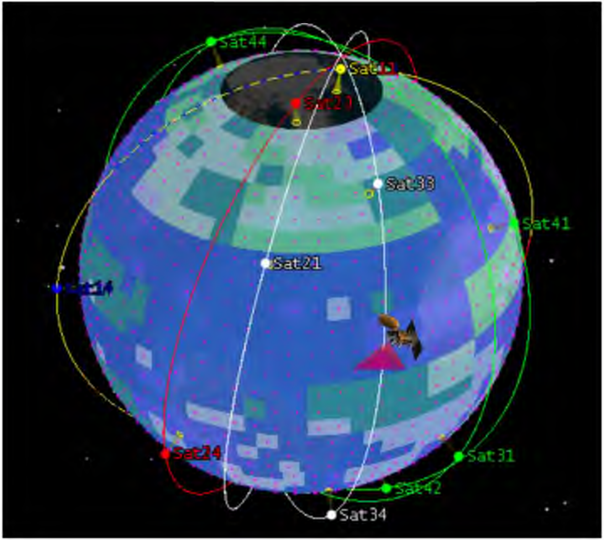

TAT-C Orbital Simulator

“Comb” Viewing ↦ Single Platform

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"Comb" Viewing $\mapsto$ Constellation

Trade-off Space: Coverage vs. Resolution

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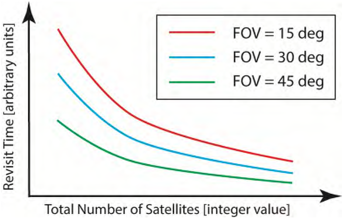
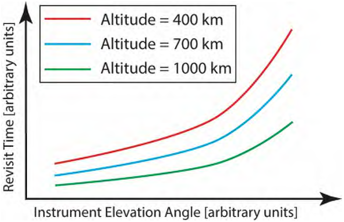
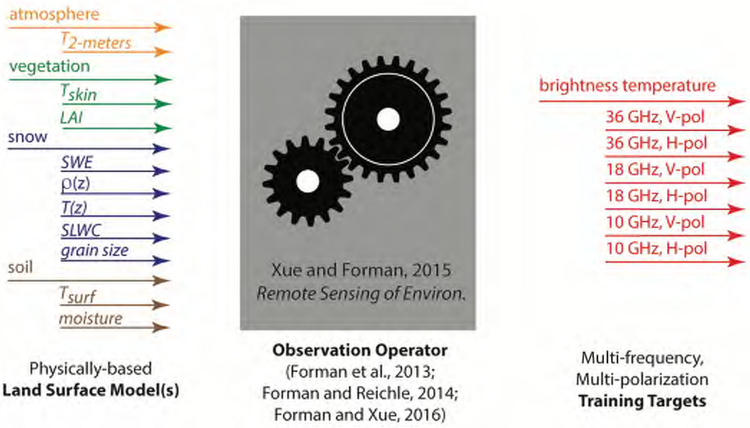




- Explore trade-off between engineering and science
  - Field-of-View (FOV)?
  - Platform altitude?
  - Repeat cycle?
  - Single platform vs. constellation?
  - Orbital configuration(s)?
- How do we get the most scientific bang for our buck?

Machine Learning "Emulators"



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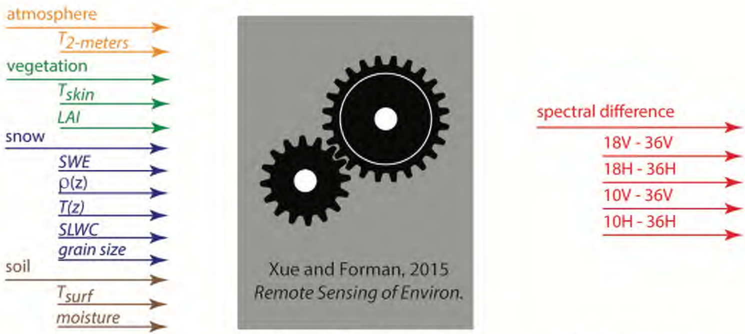

Physically-based
Land Surface Model(s)

Observation Operator
(Forman et al., 2013;
Forman and Reichle, 2014;
Forman and Xue, 2016)

Multi-frequency,
Multi-polarization
Training Targets

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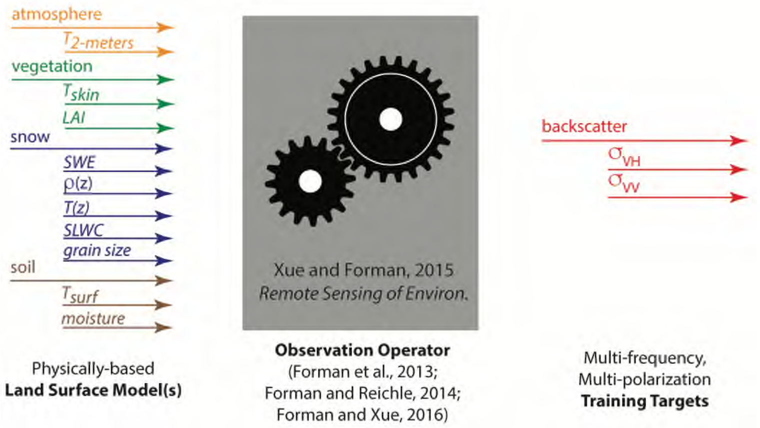
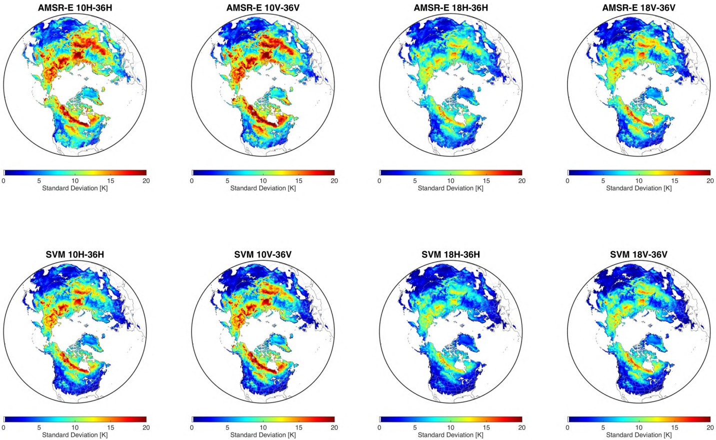


Spatiotemporal Variability



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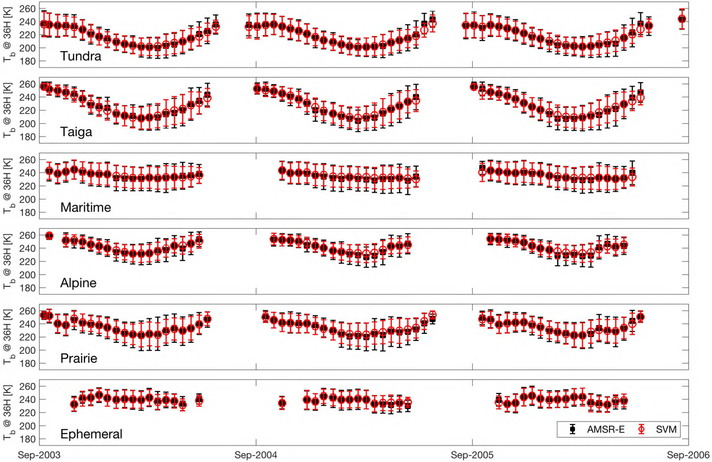

Relevancy Scenarios

- **Scenario 1**: Benchmark Analysis
  - Passive MW Assimilation <u>only</u>
- **Scenario 2**: Comparative Analysis
  - Passive MW vs. Active MW vs. LIDAR
- **Scenario 3**: Multi-sensor Analysis
  - single-sensor platform
  - multi-sensor platform
  - constellation of sensors

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Research Summary

- Global snow mission will require evidence of achievable science via OSSE . . . or some other means
- NASA LIS provides "nature run" plus assimilation framework
- TAT-C provides spatiotemporal sub-sampling of observations, including cost estimates and risk assessments
- Machine learning maps model state(s) into observation space (i.e., T_b and σ_0)
  - Enables integration of T_b, σ_0, and δh in geophysical realm (i.e., SWE and snow depth)
  - Multiple frequencies/polarizations/observations allow for flexibility and modularity in DA framework
- Snow OSSE is on-going $\longrightarrow$ open to ideas + suggestions!

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Thank You.

Questions and/or Comments?

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NASA GRACE-FO Science Team (NNX16AF17G)
NASA High Mountain Asia Science Team (NNX17AC15G)

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UMD's Division of Information Technology

SVM Mathematical Framework (1 of 2)

For parameters $C > 0$ and $\varepsilon > 0$, the **standard (primal)** form is:

$$
\begin{aligned}
\underset{\mathbf{w},\ \delta,\ \boldsymbol{\xi},\ \boldsymbol{\xi}^*}{\text{minimize}} \quad & \frac{1}{2}\langle \mathbf{w} \cdot \mathbf{w} \rangle + C \sum_{i=1}^{m} (\xi_i + \xi_i^*) \\
\text{subject to} \quad & \langle \mathbf{w} \cdot \phi(\mathbf{x}_i) \rangle + \delta - z_i \leq \varepsilon + \xi_i \\
& z_i - \langle \mathbf{w} \cdot \phi(\mathbf{x}_i) \rangle - \delta \leq \varepsilon + \xi_i^* \\
& \xi_i, \xi_i^* \geq 0, i = 1, 2, \ldots, m.
\end{aligned}
$$

where m is the available number of T_b measurements in time (for a given location in space), z_i is a T_b measurement at time i, and $\boldsymbol{\xi}$ and $\boldsymbol{\xi}^*$ are slack variables.

SVM Mathematical Framework (2 of 2)

Primal optimization is commonly solved in **dual form** as:

$$\begin{aligned}
\underset{\alpha_i,\,\alpha_i^*}{\text{minimize}} \quad & \frac{1}{2}\sum_{i,j=1}^{m}\left(\alpha_i-\alpha_i^*\right)\left(\alpha_j-\alpha_j^*\right)\langle\phi(\mathbf{x}_i)\cdot\phi(\mathbf{x}_j)\rangle \\
& +\varepsilon\sum_{i=1}^{m}\left(\alpha_i+\alpha_i^*\right)-\sum_{i=1}^{m}z_i\left(\alpha_i-\alpha_i^*\right) \\
\text{subject to} \quad & \sum_{i=1}^{m}\left(\alpha_i-\alpha_i^*\right)=0, \\
& \alpha_i\,,\,\alpha_i^*\in[0\,,\,C]\,,\ i=1,2,\ldots,m
\end{aligned}$$

where α_i and α_i^* are Lagrangian multipliers, $\langle\phi(\mathbf{x}_i)\cdot\phi(\mathbf{x}_j)\rangle$ is the inner dot product of $\phi(\mathbf{x}_i)$ and $\phi(\mathbf{x}_j)$, ε is the specified error tolerance, and C is a positive constant that dictates a penalized loss during training.