# Automatic Adaptation to Sensor Replacements

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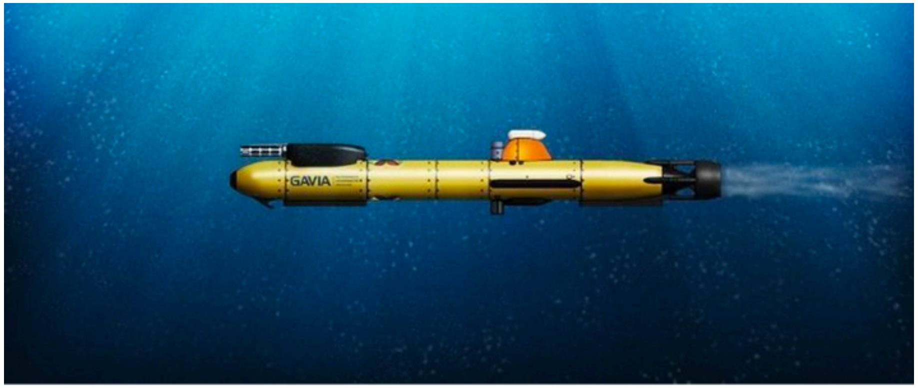
# Motivation




Unmanned Underwater Vehicle (UUV)


Self-driving Car

**Challenges for software systems**:
- Changing and uncertain environment
- System failures and changes

How to build **long-lived, survivable** software systems?
- Significantly reducing maintenance cost
- Goal of the DARPA BRASS (Building Resource Adaptive Software Systems) program

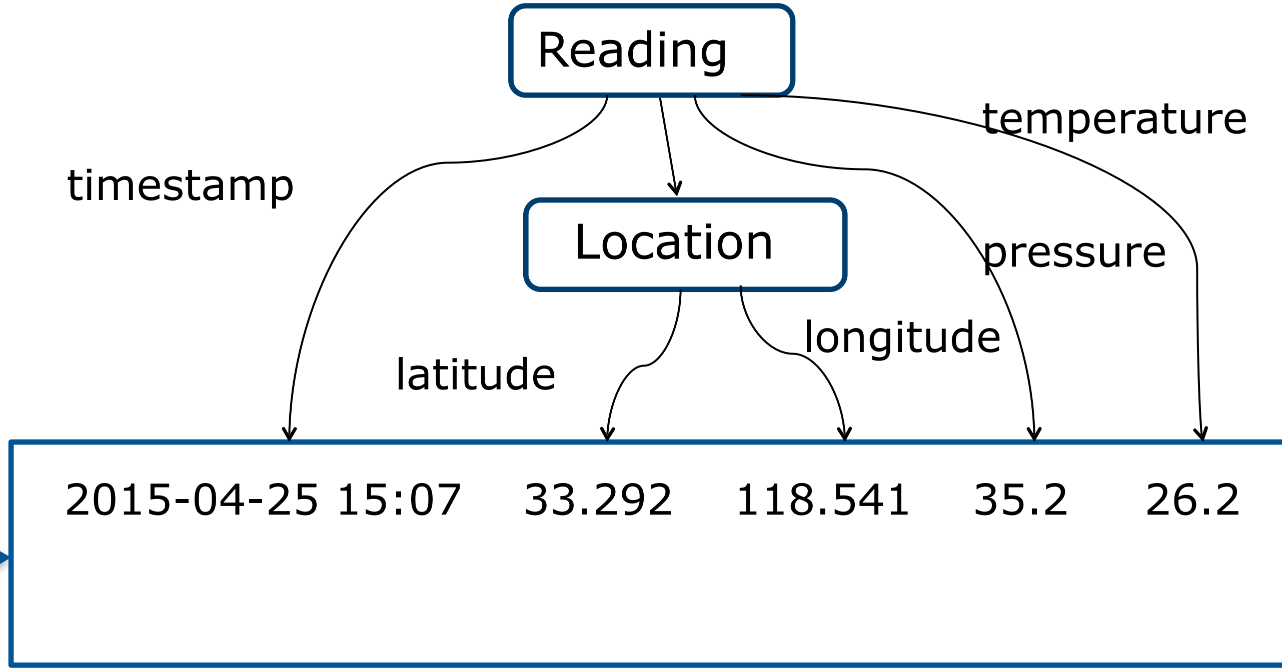
# Motivation

- Our focus: **adaptation to sensor replacements**
  - A set of sensors are replaced by new sensors
  - Causes: replacement of failed sensors, sensor upgrade, energy optimization, etc.

- Extension of our previous work [Yuan and Craig, IJCAI'17] that can be used to exploit a single new sensor

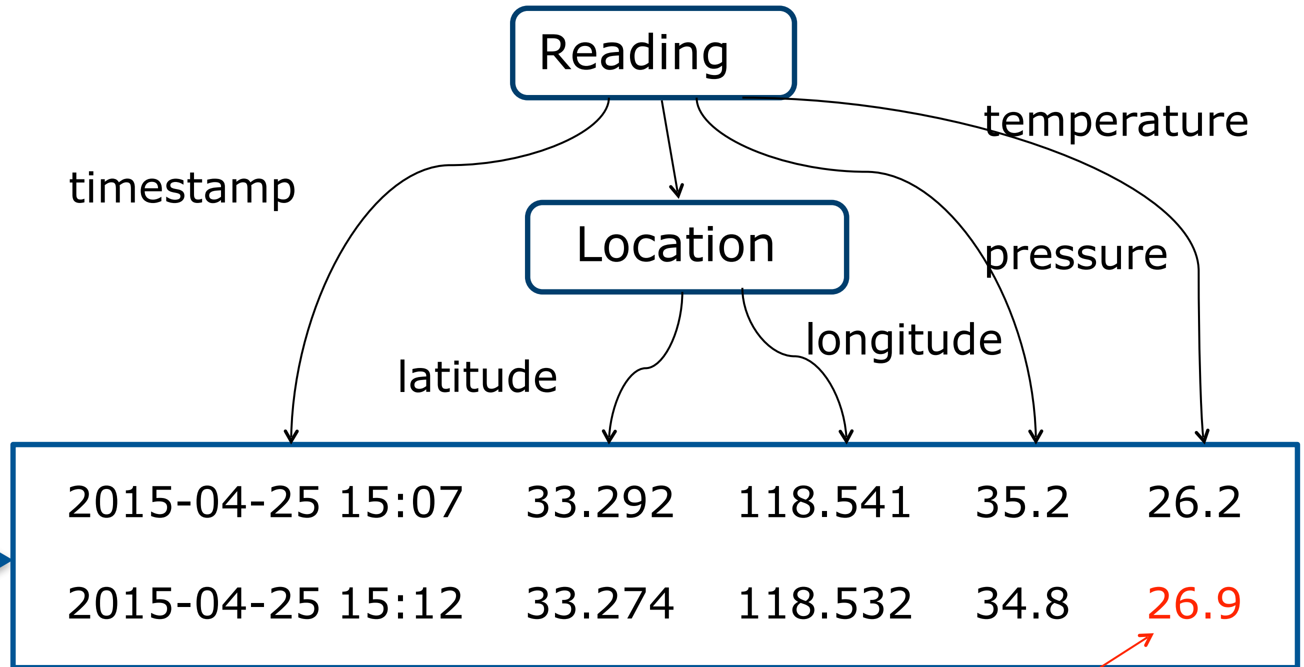
# Real-world Example of Sensor Replacement

Compound Sensor



# Real-world Example of Sensor Replacement

Compound Sensor




Replaced by a new temperature sensor

# Real-world Example of Sensor Replacement

Reading
timestamp
Location
latitude
longitude
pressure
temperature

Compound Sensor

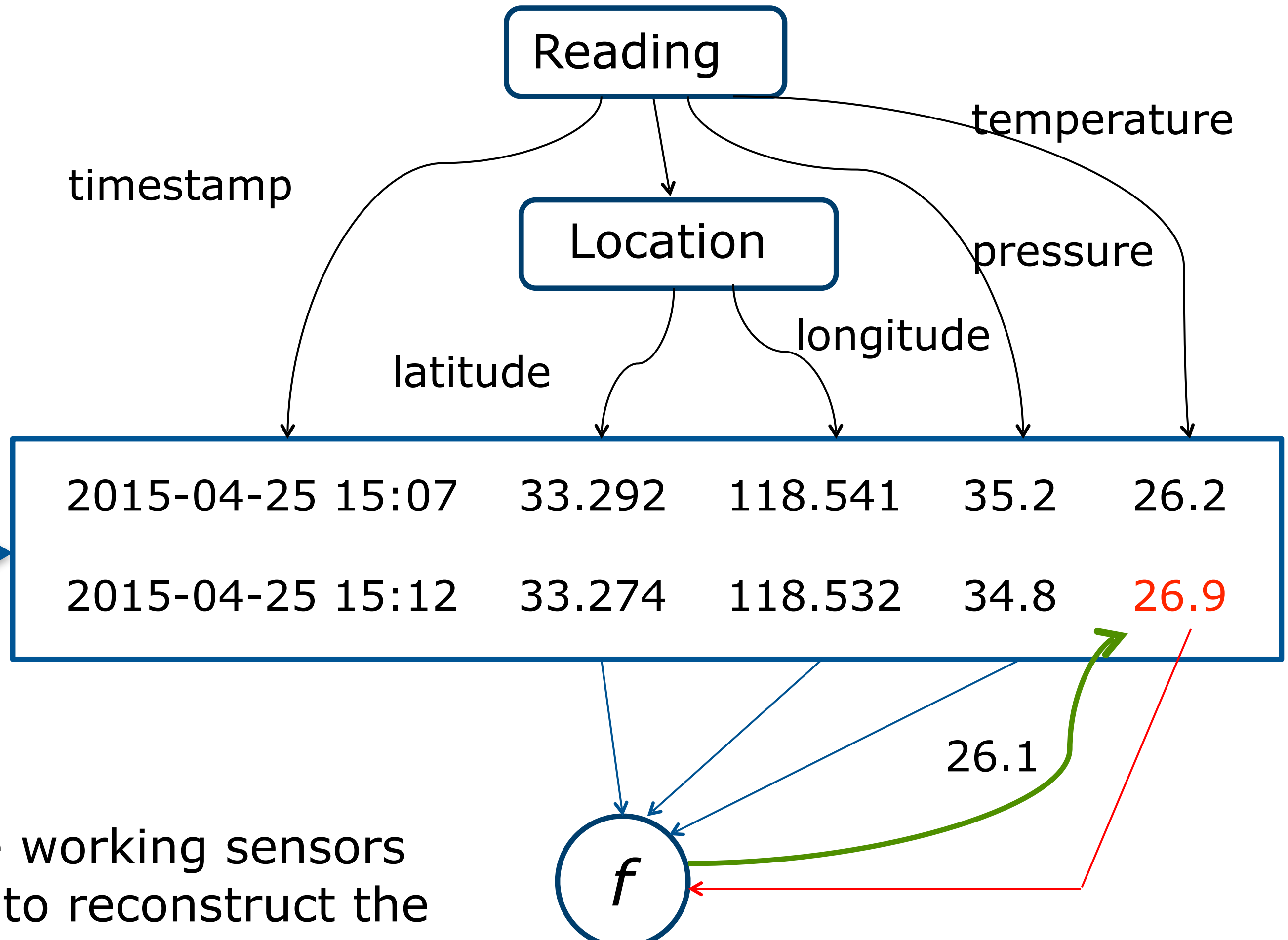
| | | | | |
|---|---|---|---|---|
| 2015-04-25 15:07 | 33.292 | 118.541 | 35.2 | 26.2 |
| 2015-04-25 15:12 | 33.274 | 118.532 | 34.8 | 26.9 |

Replaced by a new temperature sensor

Direct replacement can be bad!

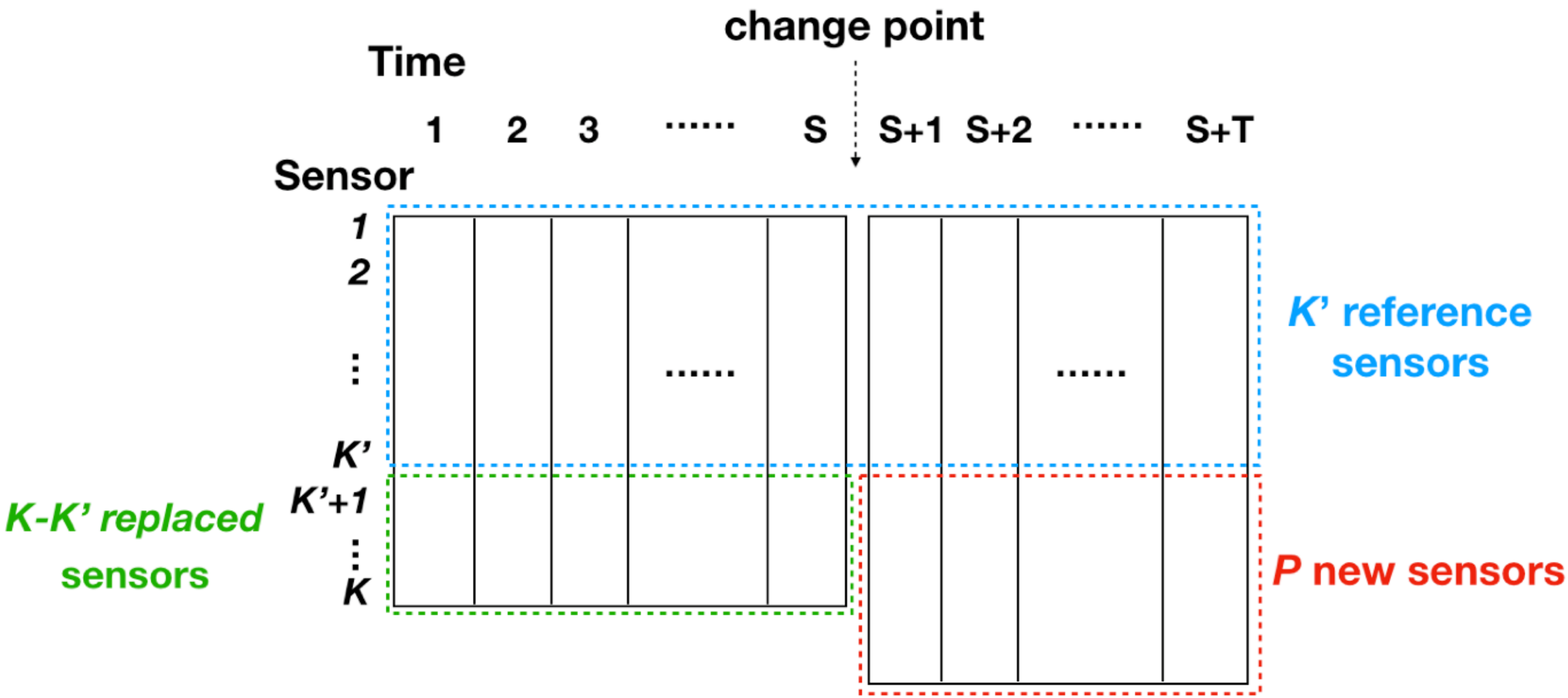
# Real-world Example of Sensor Replacement

Compound Sensor




Can we combine the working sensors and the new sensor to reconstruct the original temperature?

# Notations of Sensor Replacements



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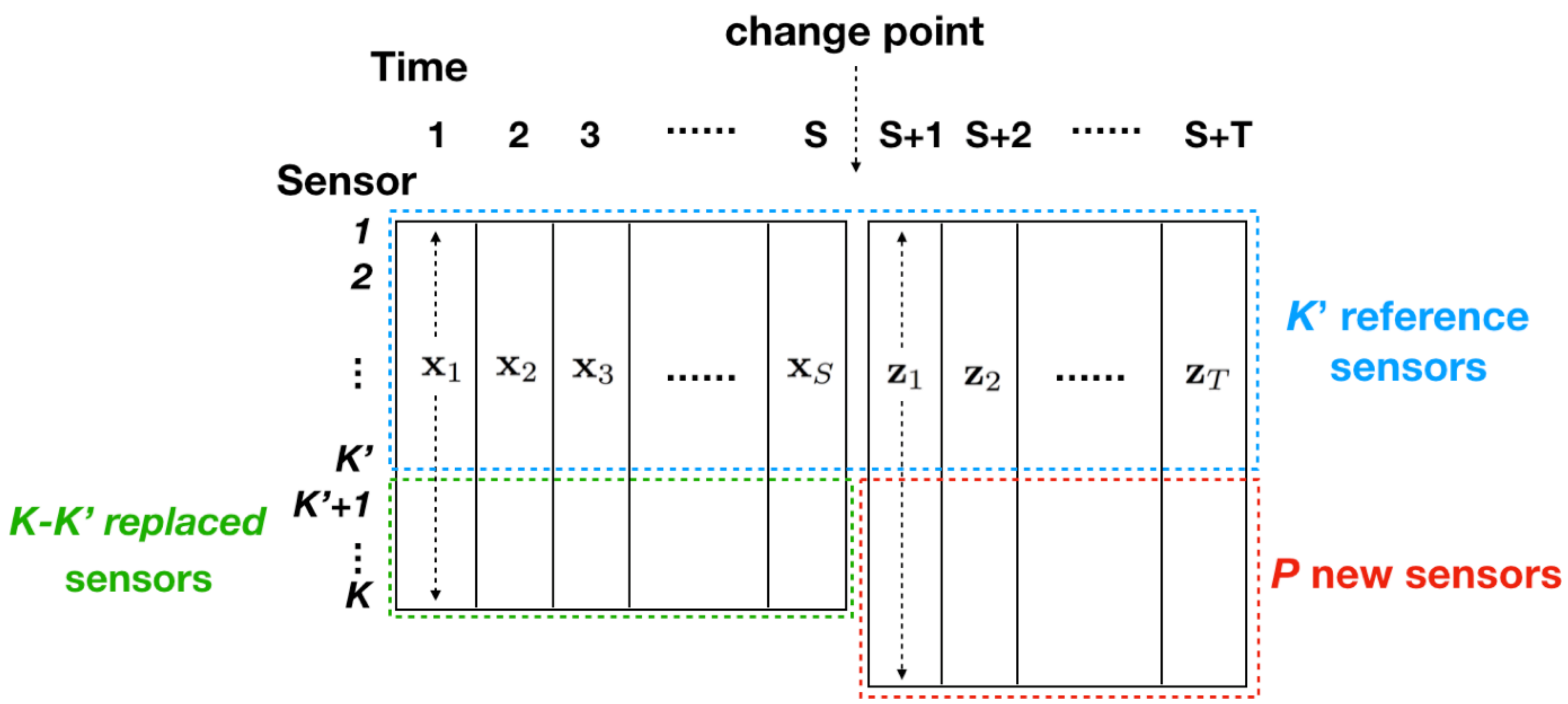
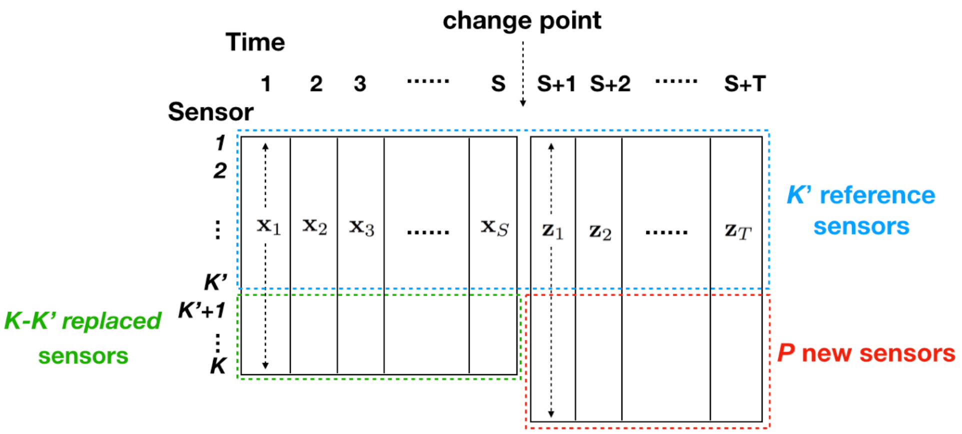


# Adaptation to Sensor Replacements

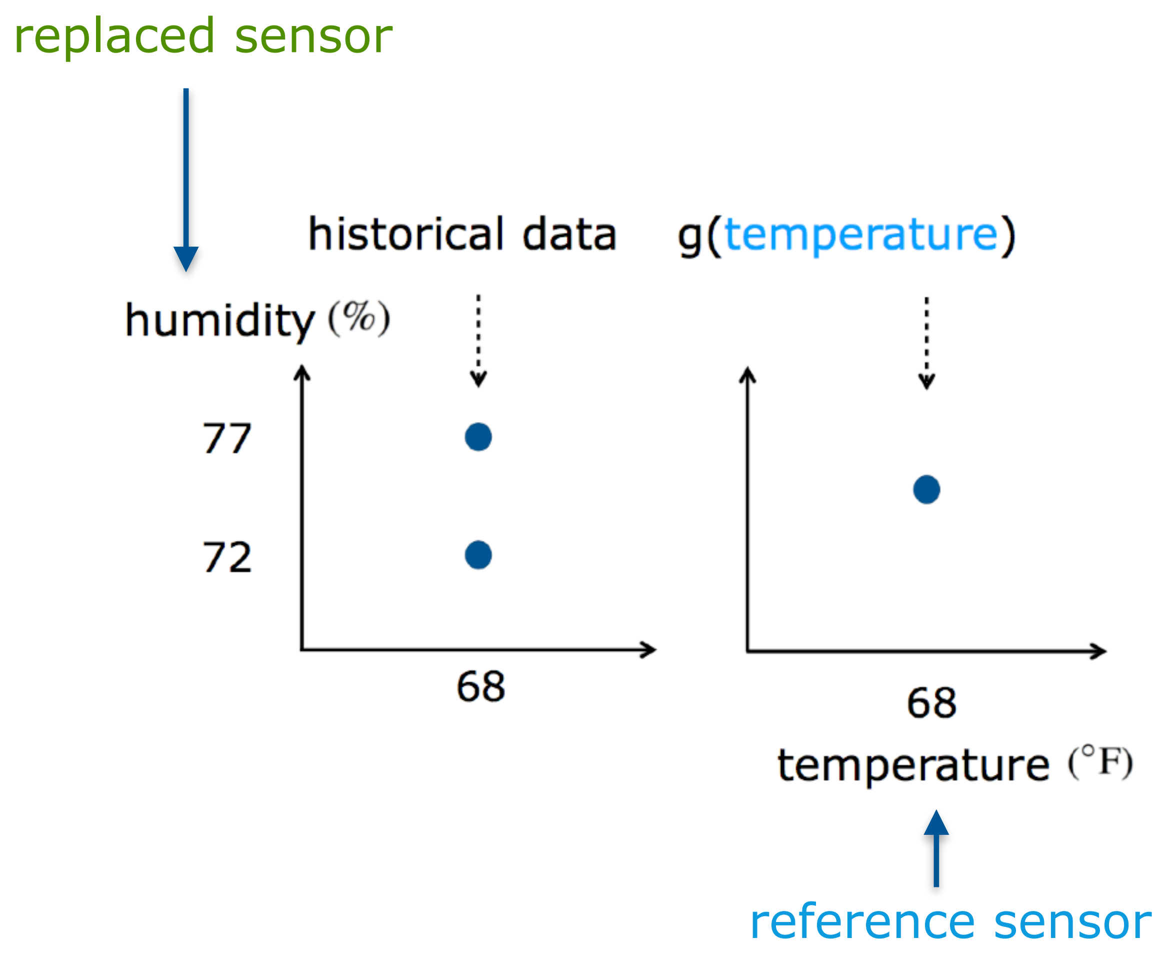
**Unexplored in previous work**



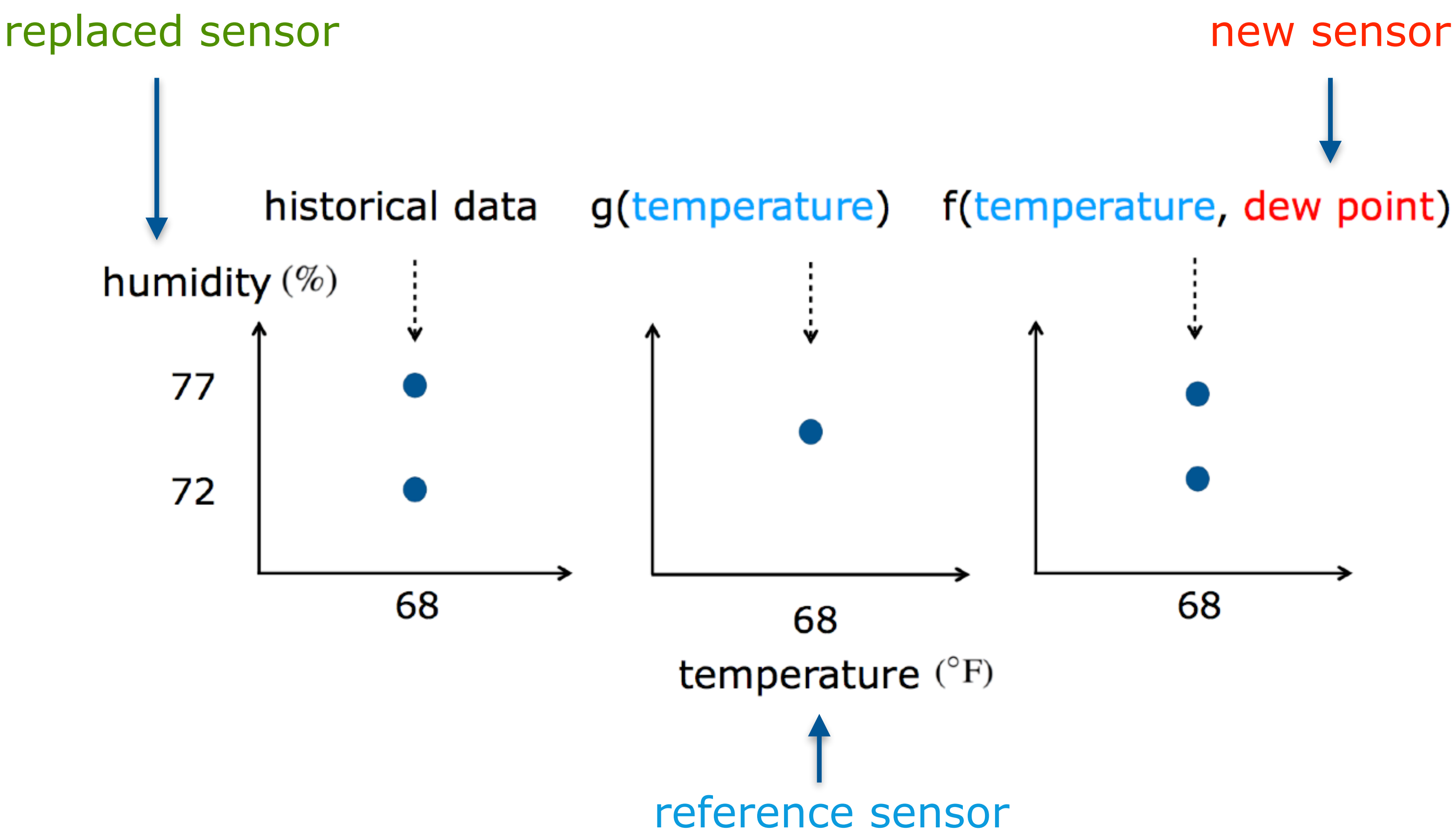

**Goal**: learning a **reconstruction function**:

f(reference sensors, new sensors) $\longrightarrow$ replaced sensors

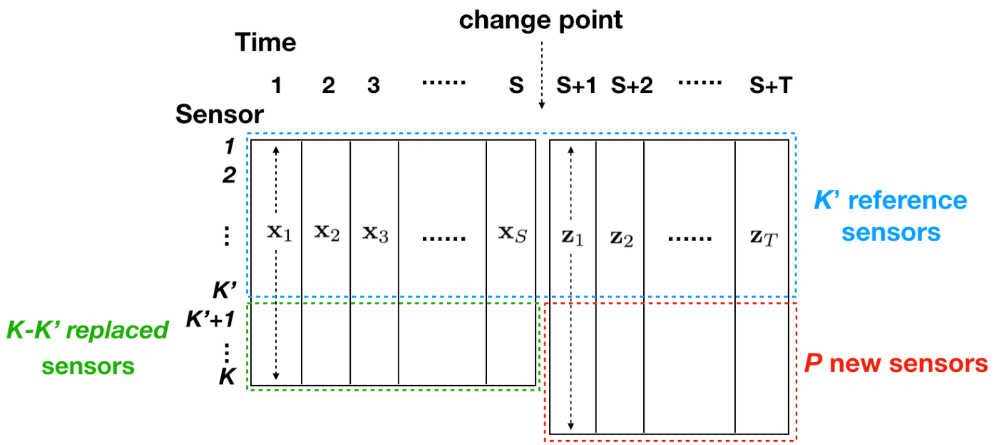
# Intuition of Exploiting New Sensors



# Intuition of Exploiting New Sensors



# Adaptation to Sensor Replacements

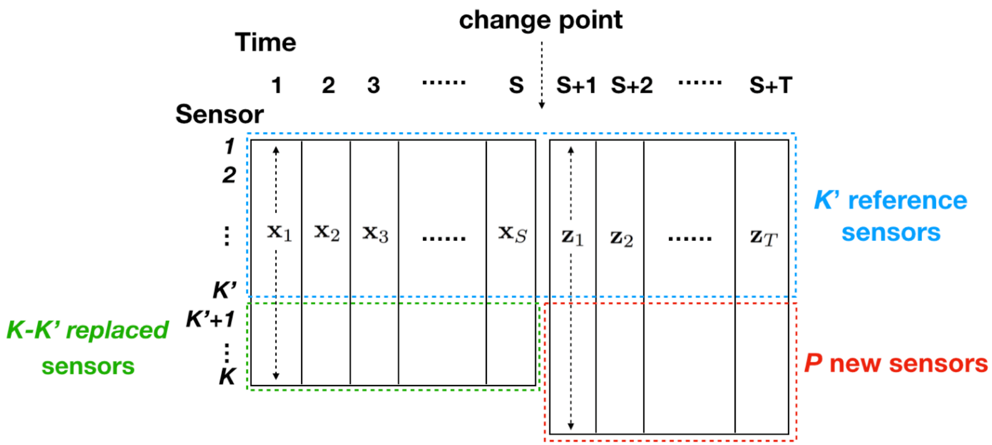



**Unexplored in previous work**

Reconstruction function:
f(reference sensors, new sensors) $\longrightarrow$ replaced sensors

**Challenge**: **no overlapping** between the replaced sensors and new sensors

# Adaptation to Sensor Replacements




**Unexplored in previous work**

Reconstruction function:
f(reference sensors, new sensors) ⟶ replaced sensors

**Challenge**: **no overlapping** between the replaced sensors and new sensors

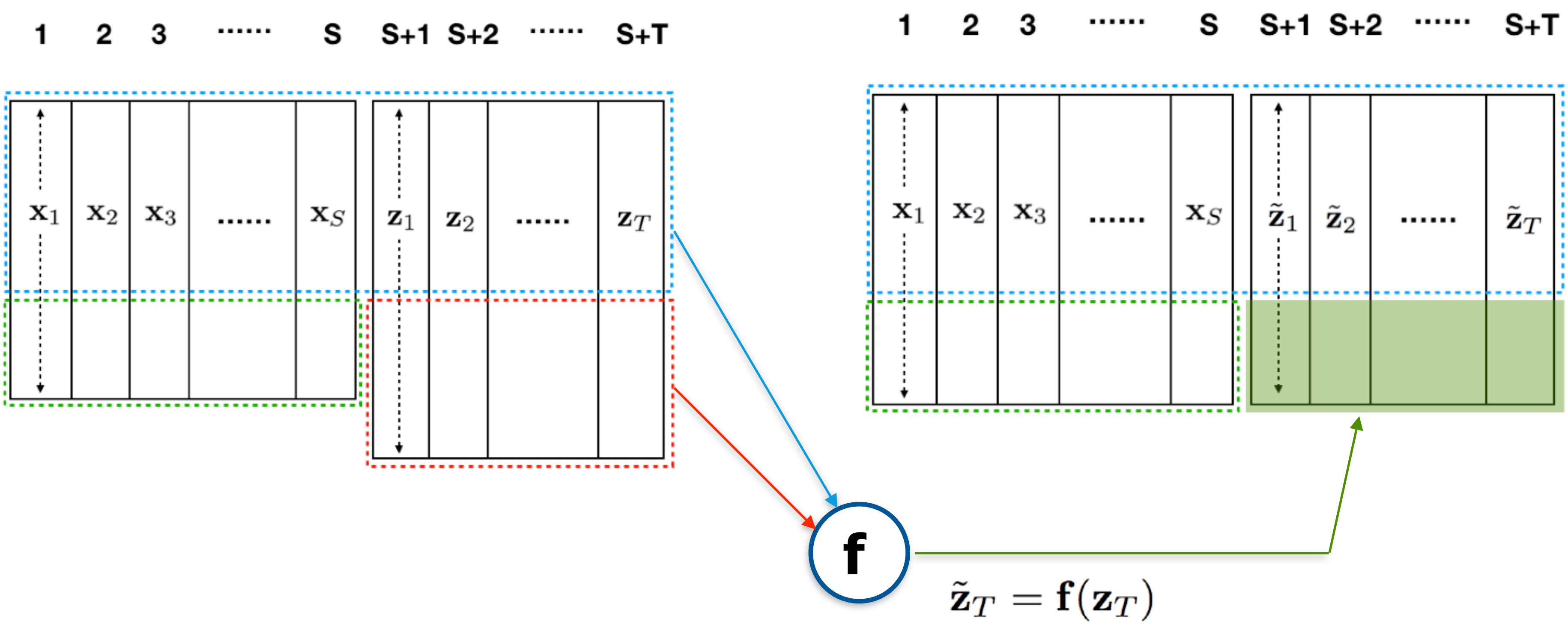
**Idea**: using the reference sensors as a bridge

**Assumption**:

**1.** Sensor values from reference sensors are correlated with those from replaced sensors

**2.** Sensor values from reference sensors are correlated with those from new sensors

# Methodology of Our Approach



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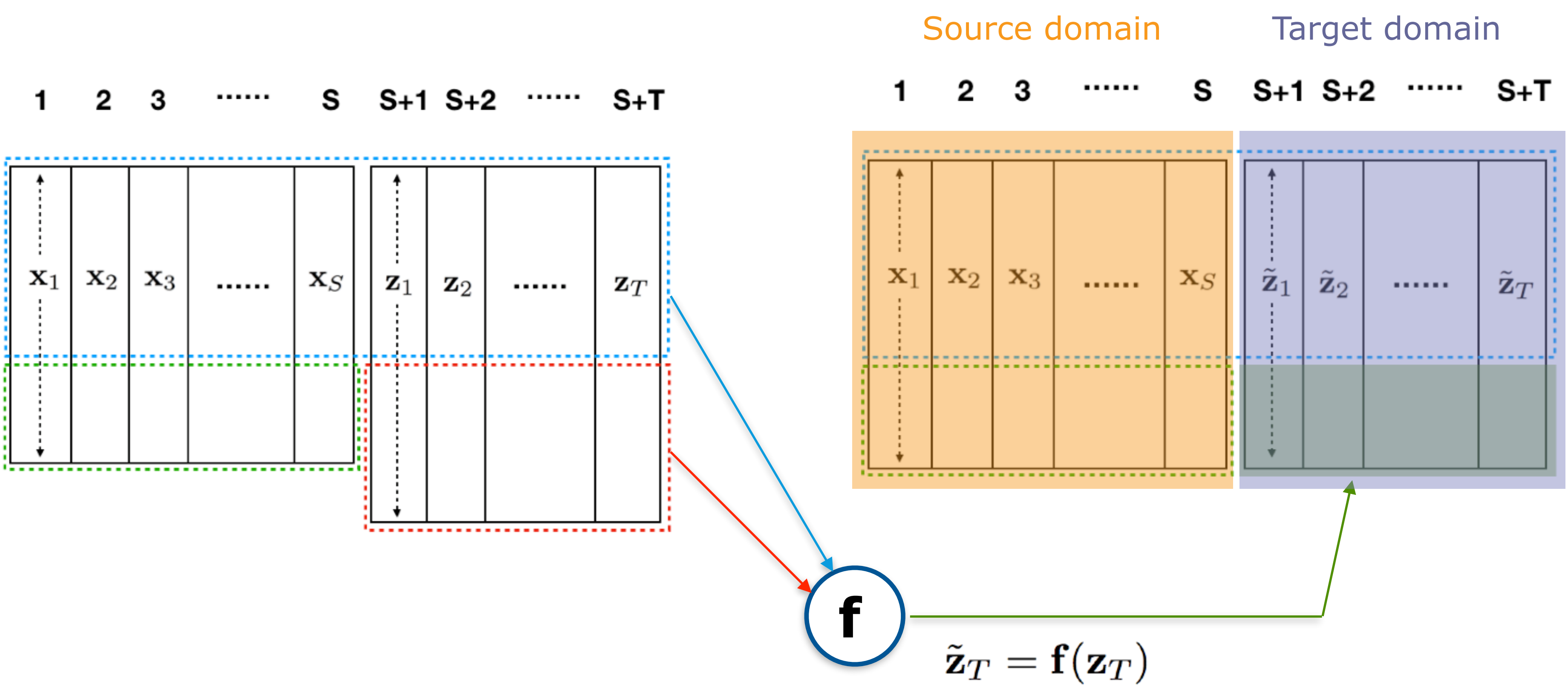
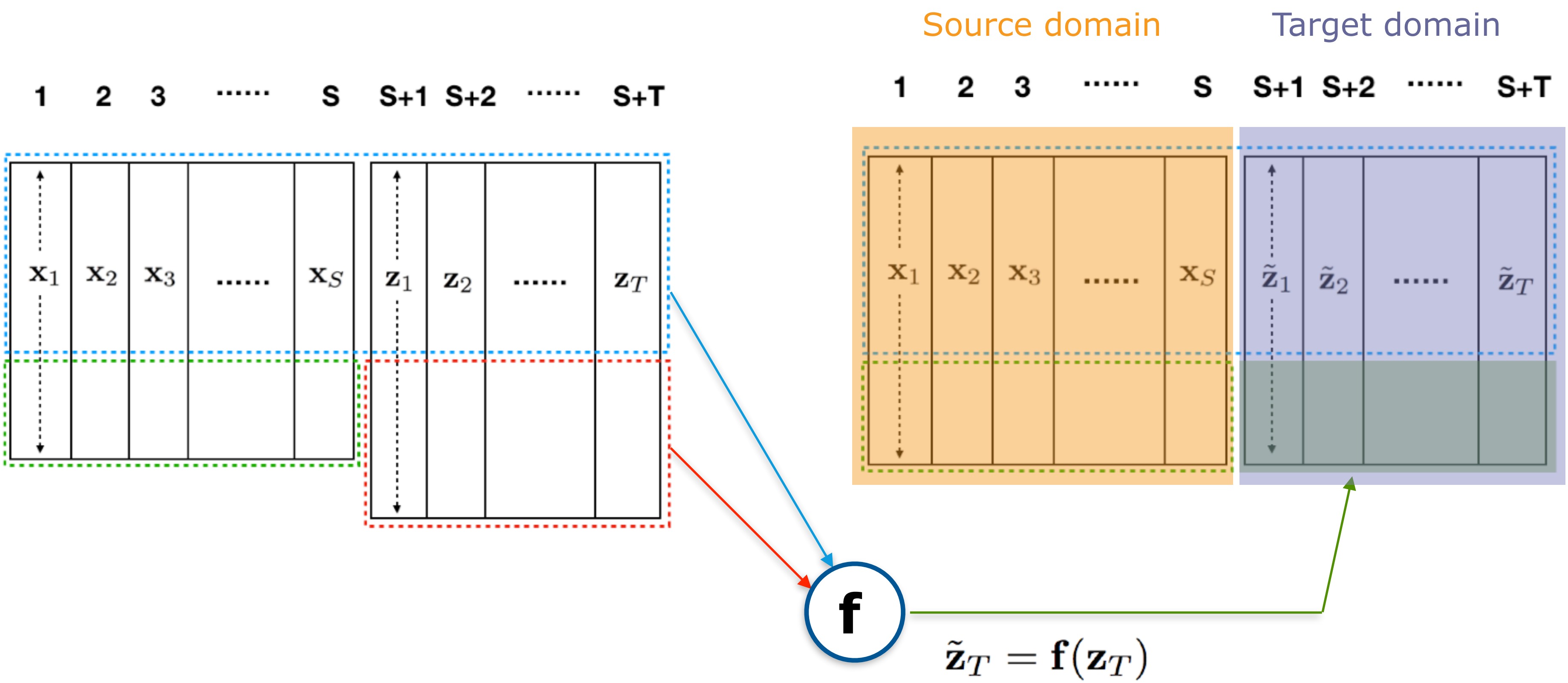


# Methodology of Our Approach

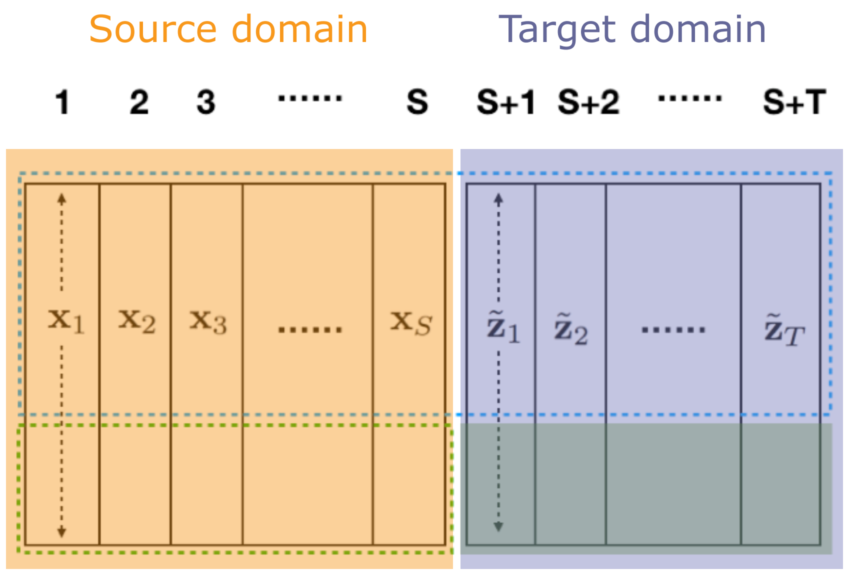
Samples in the two domains distribute similarly



# Methodology of Our Approach

Samples in the two domains distribute similarly

Two sets of samples mixed as much as possible




Minimize cross-domain *k*-nearest neighbor distances

$$\min_{\theta} \sum_{s} \sum_{t\in\mathcal{N}_{T}^{k}(s)} \mathcal{D}(\mathbf{x}_s, \tilde{\mathbf{z}}_t) + \sum_{t} \sum_{s\in\mathcal{N}_{S}^{k}(t)} \mathcal{D}(\tilde{\mathbf{z}}_t, \mathbf{x}_s)$$

$\mathbf{x}_s$'s *k* neighbors in the target domain

$\tilde{\mathbf{z}}_t$'s *k* neighbors in the source domain

# Formulation and Optimization

$$\min_{\boldsymbol{\Theta}} \sum_{s=1}^{S} \sum_{t \in \mathcal{N}_{\mathcal{T}}^{k}(s)} \mathcal{D}(\mathbf{x}_s, [\mathbf{z}_{t,1:K'}; \mathbf{f}_{\boldsymbol{\Theta}}(\mathbf{z}_t)]) + \sum_{t=1}^{T} \sum_{s \in \mathcal{N}_{\mathcal{S}}^{k}(t)} \mathcal{D}([\mathbf{z}_{t,1:K'}; \mathbf{f}_{\boldsymbol{\Theta}}(\mathbf{z}_t)], \mathbf{x}_s) + \lambda \|\boldsymbol{\Theta}\|_2^2$$

$$\mathbf{f}_{\boldsymbol{\Theta}}(\mathbf{z}) = \boldsymbol{\Theta}^{\mathrm{T}} \mathbf{h}(\mathbf{z})$$

regularization term

non-smooth in $\boldsymbol{\Theta}$, because neighbors are dependent on $\boldsymbol{\Theta}$

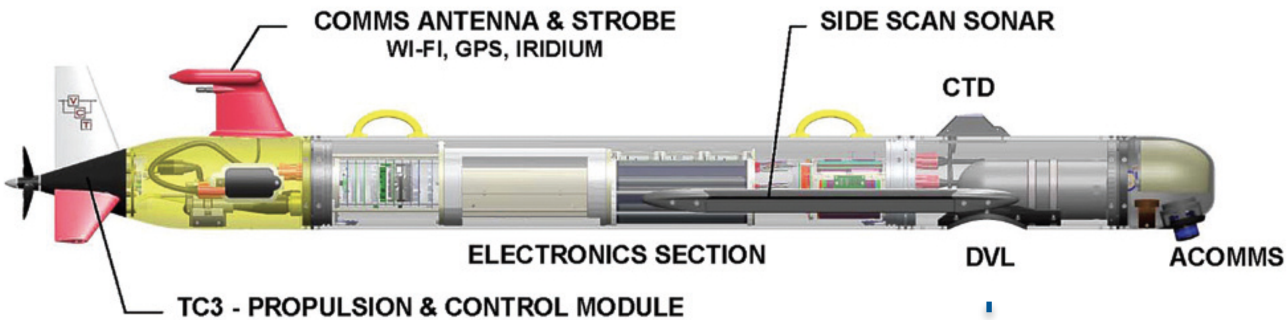
Alternating Optimization (EM-like algorithm):

- Fix $\boldsymbol{\Theta}$, update neighbors $\mathcal{N}_{\mathcal{T}}^{k}(s)$ and $\mathcal{N}_{\mathcal{S}}^{k}(t)$
- Fix neighbors $\mathcal{N}_{\mathcal{T}}^{k}(s)$ and $\mathcal{N}_{\mathcal{S}}^{k}(t)$, update $\boldsymbol{\Theta}$

# Results on UUV Data

A UUV travels from a starting point to an end point in a simulated environment

**Sensors**: propeller RPM, waterspeed, DVL (surge, heave, sway, pitch, roll, depth, heading)




surge, heave, sway, pitch, roll, depth, heading

# Results on UUV Data: Individual Sensor Replacement

**Replaced sensor**: surge/heave/sway
**New sensor**: biased version of surge/heave/sway
**Reference sensors**: remaining sensors

Directly using the new sensor

Adaptation using the reference sensors only

Adaptation using the reference sensors and predicted values of the new sensors

| Sensor | **Replace** | **Refer** | **Refer-Z** | **ASC** | Imp.(%) |
|---|---|---|---|---|---|
| surge | 2.47 | 0.66 | 0.58 | 0.47 | 18.9 |
| heave | 0.13 | 0.020 | 0.020 | 0.019 | 6.5 |
| sway | 2.31 | 0.74 | 0.72 | 0.71 | 1.1 |

Our approach

Reconstruction errors (RMSE) averaged over 20 simulated trips

**ASC** achieves an average improvement of 8.8% over the competing methods

# Results on UUV Data: Compound Sensor Replacement

**Replaced sensors**: all DVL sensors
**New sensor**: biased version of surge, heave and sway
**Reference sensors**: remaining sensors (propeller RPM, waterspeed)

Directly using the new sensor

Adaptation using the reference sensors only

Adaptation using the reference sensors and predicted values of the new sensors

| Sensor | **Replace** | **Refer** | **Refer-Z** | **ASC** | Imp.(%) |
|---|---|---|---|---|---|
| surge | 2.47 | 0.71 | 0.67 | 0.62 | 6.0 |
| heave | 0.094 | 0.026 | 0.026 | 0.024 | 3.4 |
| sway | 2.31 | 0.78 | 0.75 | 0.75 | -0.5 |

Our approach

Reconstruction errors (RMSE) averaged over 20 simulated trips

**ASC** achieves an average improvement of 3.0% over the competing methods

# Results on Weather Data

## Weather Underground Data

30 weather stations from 10 geographical clusters

**Sensors**: temperature, dew point, humidity, wind speed, wind gust, pressure

Compared to baselines, our approach **ASC** achieves

**6.4%** improvement for **individual sensor replacements**

**5.7%** improvement for **compound sensor replacements**

# Further Improvements

- **Dealing with many sensors**
  - Challenging due to more noise in sensor values
  - **Approach**: select a subset of the reference sensors and new sensors that are well correlated with the replaced sensors
- **Estimating adaptation quality**
  - Useful for upper-level software
  - **Approach**: produce an error interval instead of a single reconstruction value

# Related Work

- **Detecting Sensor Failures and Changes**
  - Change point detection [Aminikhanghahi and Cook '16] [Pimentel et al., '14]
    - Distribution-based [Kawahara and Sugiyama, '12] [Harchaoui et al., '09] [Yamanishi and Takeuchi, '02]
    - Reconstruction-based [Crook et al., '02] [Singh and Markou, '04] [Ide and Tsuda, '07] [Chatzigiannakis et al., '06]
    - Probabilistic [Adams and MacKay, '07] [Saatci et al., '10] [Dereszynski and Dietterich, '12] [Dietterich et al. '12]
    - Distance-based [Angiulli and Pizzuti, '02] [Bay and Schwabacher, '03] [Chawla and Sun, '06] [Keogh et al., '01] [Ide et al., '13] [Budalakoti et al., '06] [Chen et al., '15]

Most detection methods do not address how to automatically adapt to failures or changes

- **Reconstruction of Sensor Values**
  - Some probabilistic methods [Dereszynski and Dietterich, '12] [Dietterich et al. '12] can be used to reconstruct changed sensor, but cannot leverage new sensors
  - Our earlier work [Yuan and Craig, '17] can only exploit a single new sensor

Our approach can adapt to multiple new sensors, which are not possible by existing approaches

# Conclusion

- A novel problem of automatically adapting to sensor replacements
  - In the context of building long-lived, survivable software
- A machine learning approach capable of
  - Exploiting new sensors
  - Scaling to many sensors
  - Estimating the adaptation quality

  - Supported by empirical study in the UUV and weather domains