TECHNOLOGY
OFFER

Calibration Model Maintenance

Goes Unsupervised …

Calibration model maintenance is the key ingredient to keep your process monitoring and offline sensor systems operational and reliable over time and upon changing instrumental, environmental or process-associated conditions. By leveraging recent advances in Transfer Learning (TL), Bottleneck Analytics offers a comprehensive portfolio of algorithms and workflows to assist in calibration model maintenance that is unique in the industry.

Model Maintenance vs. Re-calibration

Multivariate calibration models are an integral part of most state-of-the-art process monitoring systems and thus key enablers of the digital transformation in a wide range of industries (e.g. chemical/pharmaceutical/ food). It turns out that such data-driven models tend to be susceptible to small changes in instrumental response, environmental or process-associated conditions (e.g. caused by a change in raw material composition) leading to invalid predictions and eventually wrong decisions. When calibration models become outdated, most decision makers tend to go through the entire process of acquiring new data and building new calibrations from scratch (i.e. re-calibration) instead of leveraging *prior knowledge* in order to save resources when maintaining their models.

Transfer Learning (TL)

TL is the branch of Machine Learning (ML) concerned with transferring knowledge extracted from data in one domain to another, related domain (e.g. between similar industrial processes). The main promise of TL is that ML models don‘t have to be developed from scratch for similar tasks thereby saving resources in terms of annotated data which might not always be available in sufficient amounts or are otherwise expensive to obtain.

Our Approach

The products offered by Bottleneck Analytics leverage recent advances in TL and are designed around the concept of domain-invariant *Latent Variables* (LVs). In particular, our approach models the property of interest (e.g. analyte concentration) based on LVs that are invariant across related domains in order to maintain or adapt calibrations either to new environmental/process conditions or measurement devices (i.e. calibration transfer). The main asset of our technology lies in the fact that model maintenance can be undertaken using either (partially) labeled (semi -supervised) or entirely unlabeled data (unsupervised), which reduces the need for expensive and time-consuming data annotation efforts (e.g. reference analytics). Figure 1 exemplifies the concept of domain-invariant LVs for calibration model maintenance.

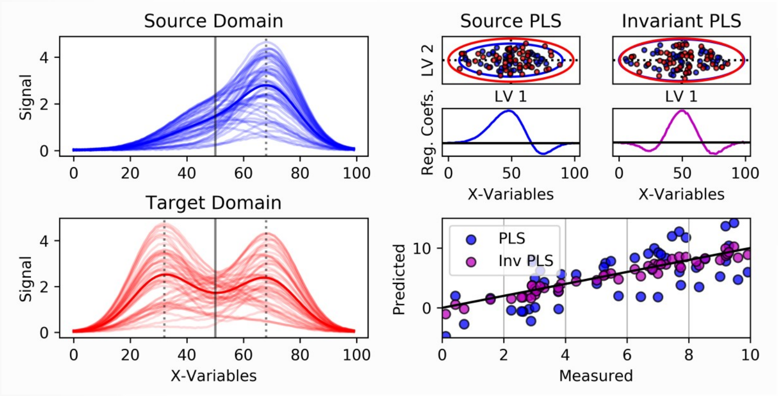

Figure 1: Model adaptation from a source (blue) to a target (red) domain. Left: Hypothetical data. Top right: Projections and regression coefficients corresponding to an ordinary and an invariant partial least squares (PLS) model. Bottom right: Predictions of ordinary (blue) and invariant (magenta) model on target domain data.

Bottleneck Analytics GmbH
Doing More with Less

Key-values/Features and Benefits

- **Un- and Semi-supervised model maintenance**
- **Resource efficiency**
- **Model maintenance, adaptation and calibration transfer**

Fields of Application

- **Process industry**
- **IoT applications**
- **Digital health**
- **Non-destructive testing**
- **Quality control**

What we offer

- **Tailored software components**
- **Consulting**
- **Feasibility studies**
- **Calibration service**

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