

A Single Unified Method for Data-source Specific and Generalised Human Sensing Models

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Human Sensing Applications

Presence Detection and Occupancy Counting Is there anyone out there?
How many people are there?

Human Activity Recognition What are they doing? E.g., walking, falling, running, sitting, posture, gestures.

Localisation and Tracking Where is everyone (going) right now?

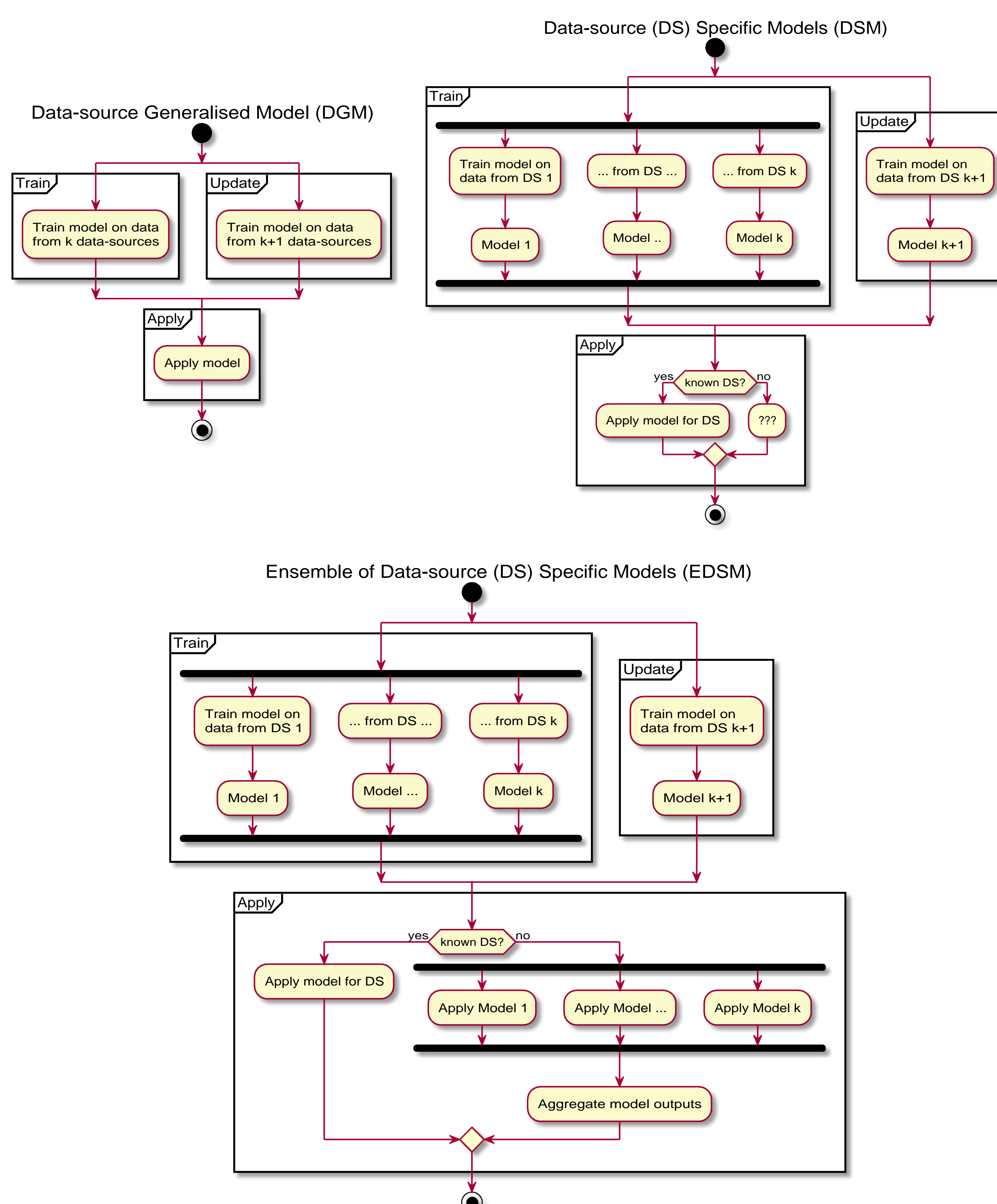
Wearable and Device-Free Sensing

On-body/wearable sensing Sensors are placed on (or in) the user's body.
Example sensors: Inertial Measurement Units, Medical/Sports Sensors (e.g., heart rate or blood pressure sensor).

Environmental/device-free sensing Sensors are placed in the user's environment. Example sensors: video cameras, microphones, light sensors, radio signals such as Wi-Fi.

Data Sources and Generalisation

- ▶ A data source (DS) can correspond to anything that causes systematic variation in the sensed data such as a specific sensing device, sensor placement (on the body or in the building), or person.
- ▶ We want models that *generalise well to **unknown** data sources* (e.g., new users or sensor boards), *without sacrificing performance for **known** data sources*.



Research Hypotheses

- ▶ A Data-source Specific Model (DSM) tends to perform better on *known* data sources than a Data-source Generalised Model (DGM).
- ▶ A DGM tends to perform better than a DSM on *unknown* data sources.
- ▶ An Ensemble of data-source specific models (EDSM) performs comparably to a DGM on *unknown* data sources, but without sacrificing performance for *known* data sources.

Results

Table: 95% Confidence Intervals for the Accuracy [%] of a DGM, EDSM, and DSM on human activity data from unknown users (DSMG), and of a DSM on data from known users. N_{ppl} denotes the number of individuals in the data set. The inference algorithm was a Gradient Boosted Tree on a set of time- and frequency-domain features extracted along a sliding window from a wearable inertial measurement unit worn in the given location.

data set	sensor	N_{ppl}	DSM	DSMG	DGM	EDSM
FUSION	wrist	10	97.3–98.5	80.5–87.9	89.9–96.9	87.2–95.8
MHEALTH	wrist	10	95.5–99.5	59.9–66.5	76.8–90.6	68.7–80.5
OPPORT	wrist	4	85.4–91.2	70.7–74.3	69.9–86.3	67.5–87.1
REALWORLD	chest	15	96.1–97.3	43.0–53.6	69.3–83.5	62.6–77.2
SAFESENS	chest	11	95.6–98.4	28.8–39.0	65.6–75.0	43.4–60.2
SIMFALL	chest	17	63.7–68.5	22.8–25.2	42.5–48.3	34.7–40.5
SIMFALL	wrist	17	60.8–66.2	22.0–24.8	38.7–46.1	32.9–40.3
UTSMOKE	wrist	11	88.3–92.3	59.4–63.8	66.5–75.5	64.4–74.6

Further Work I Hope To Conclude

- ▶ Evaluation in a device-free sensing scenario (mobility detection from received signal strength in Wi-Fi networks).
- ▶ Compare performance to methods that maintain one model for each *cluster* of similar data-sources and map data to one of them when applying the model.
- ▶ Combine DSMs whose output spaces overlap only partially (e.g., some target concepts are unavailable for some data-sources).
- ▶ Weigh contribution of DSMs to the ensemble according to DSM confidence (e.g., sample size, accuracy).

Publications

- ▶ S. Scheurer, S. Tedesco, Ò. Manzano, K. N. Brown, and B. O'Flynn. "Monitoring Emergency First Responders' Activities via Gradient Boosting and Inertial Sensor Data". In: *Europ. Conf. on Machine Learning and Principles and Practice of Knowledge Discovery in Databases*. ECML/PKDD. 2018.
- ▶ S. Scheurer, S. Tedesco, K. N. Brown, and B. O'Flynn. "Human Activity Recognition for Emergency First Responders via Body-Worn Inertial Sensors". In: *International Conference on Wearable and Implantable Body Sensor Networks*. IEEE, 2017.
- ▶ S. Scheurer, S. Tedesco, K. N. Brown, and B. O'Flynn. "Sensor and Feature Selection for an Emergency First Responders Activity Recognition System". In: *Sensors*. IEEE, 2017.

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