Activity Recognition from Wrist IMU (PAMAP2)

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1. Data source: PAMAP2 (UCI)

Dataset: *PAMAP2 Physical Activity Monitoring* (UCI Machine Learning Repository)

- **UCI dataset page (download + description):**
  - https://archive.ics.uci.edu/dataset/231/pamap2+physical+activity+monitoring

- **Local path (expected):** download and unzip the dataset into `./data/pamap2/` (the `data/` directory is not committed to git)

- **Dataset readme (format / notes):**
  - https://archive.ics.uci.edu/ml/machine-learning-databases/00231/readme.pdf

- **License:** Creative Commons Attribution 4.0 International (**CC BY 4.0**)

PAMAP2 is a public wearable-sensing dataset for **human activity recognition (HAR)**. It contains recordings from **9 subjects** performing **18 labeled activities** (plus label `0` for transient/other) while wearing three IMU sensors (**hand/wrist**, **chest**, **ankle**) and a heart-rate monitor.

File format (from the dataset readme): each row has **54 columns**: - `1` timestamp (s)
- `2` activityID
- `3` heart rate (bpm)
- `4-20` IMU hand (wrist)
- `21-37` IMU chest
- `38-54` IMU ankle

Each IMU block contains: - temperature (°C)
- 3D accelerometer (±16g) and 3D accelerometer (±6g)
- 3D gyroscope (rad/s)
- 3D magnetometer (T)
- orientation (not valid in this collection)

Activity IDs (18 activities + transient): 1 lying; 2 sitting; 3 standing; 4 walking; 5 running; 6 cycling; 7 Nordic walking;
9 watching TV; 10 computer work; 11 car driving; 12 ascending stairs; 13 descending stairs;
16 vacuum cleaning; 17 ironing; 18 folding laundry; 19 house cleaning; 20 playing soccer; 24 rope jumping;
0 other (transient activities)

What we use in this notebook: Protocol recordings only, with a **watch-like setup**: wrist IMU signals (ACC/GYRO/MAG) as inputs and the **activityID** as the multi-class label. We **exclude label `0`** ("transient/other") to keep the benchmark focused on the defined activities.

2. Load data & quick sanity checks

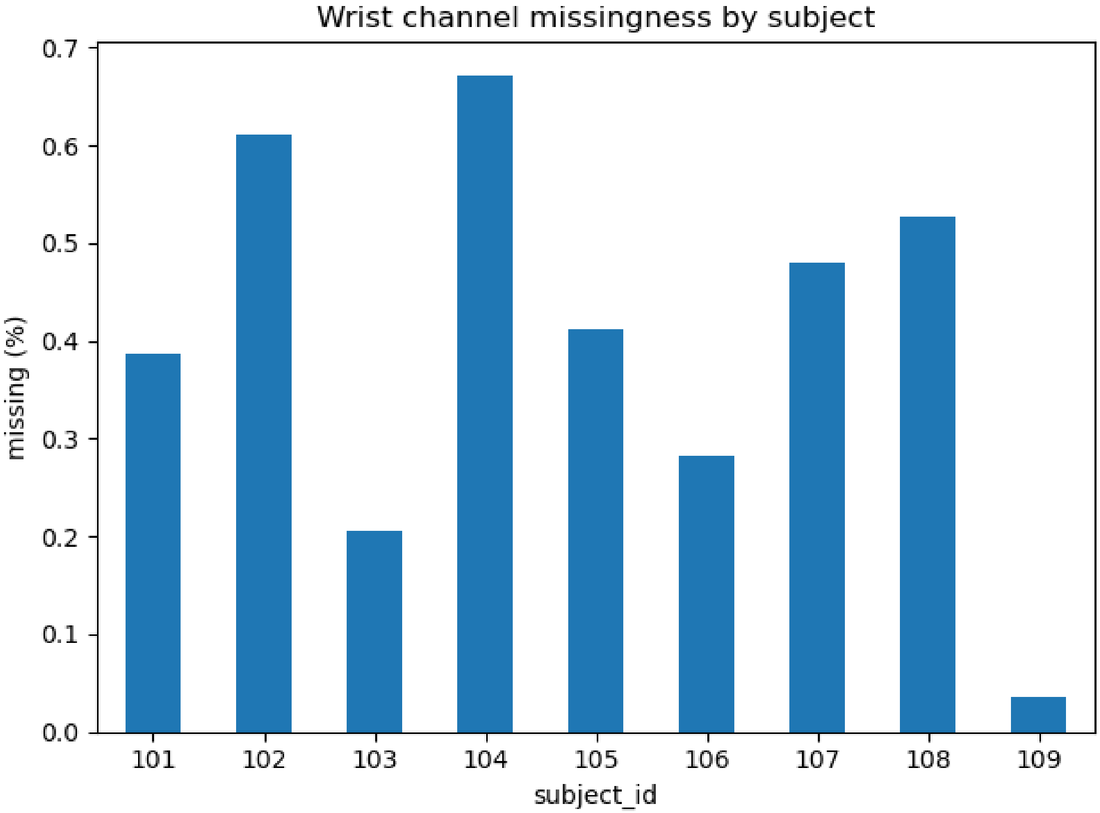
We load the **Protocol** recordings (one file per subject) from `./data/pamap2/`. The raw `.dat` files do not include column headers, so we explicitly assign the **54 columns** defined in the dataset readme. A `subject_id` is added based on the filename.

As a sanity check, we verify that the raw files match the expected **54-column** structure. After this check passes, we immediately **subset to the wrist/hand signals** plus the minimal metadata needed for HAR (timestamp_s, activity_id, subject_id). We also **drop the orientation channels** because they are stated to be **invalid** in this data collection.

Finally, we summarize **activity coverage per subject** and visualize **subject-wise missingness** for the wrist channels.

```
Raw files OK: 54 raw columns (expected 54)

            n_samples  n_activities (of 19 incl. 0: transient)
subject_id
101            376417                                        13
102            447000                                        13
103            252833                                         9
104            329576                                        12
105            374783                                        13
106            361817                                        13
107            313599                                        12
108            408031                                        13
109              8477                                         2
```



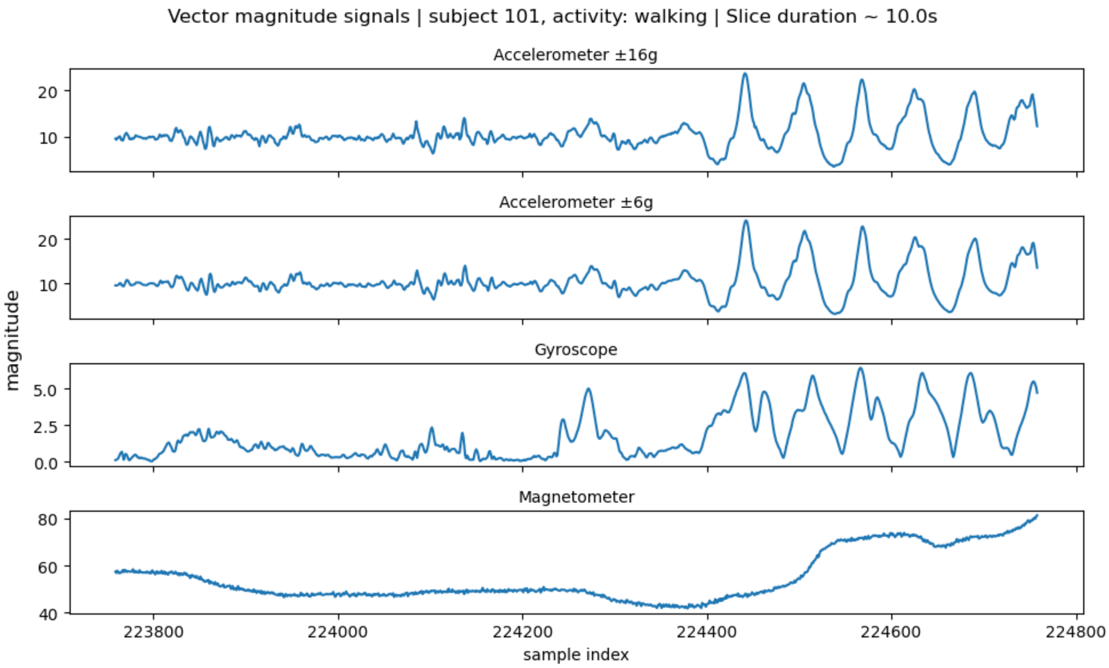
3. Preprocessing

In this section, we prepare the wrist IMU signals for windowing and feature extraction:

- We **remove transient activity samples** (`activity_id == 0`) to focus on well-defined activity classes.
- We handle **missing values** by interpolating short gaps **within each subject** and dropping any remaining missing samples.
- For each tri-axial wrist sensor, we compute the **vector magnitude** signal to provide an orientation-robust representation.

We visualize as an example, the **vector magnitude signals computed** for a short segment of one subject and one activity.

```
Preprocessed data shape: (1942872, 20)
```



4. Windowing

We segment the continuous wrist IMU signals into **fixed-length sliding windows**, which are the basic samples used for feature extraction and modeling in wearable activity recognition.

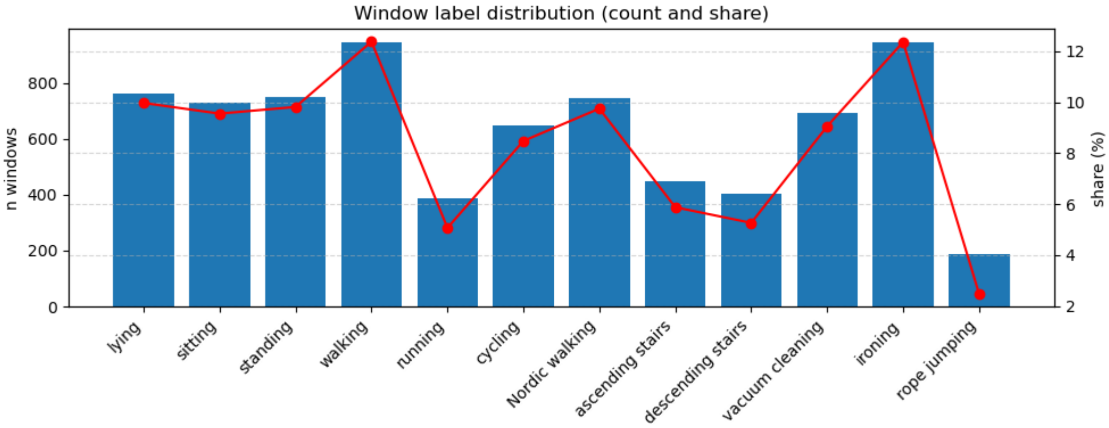
We use a **5-second window** with **50% overlap**, a common and widely accepted choice in HAR that balances temporal context with responsiveness. Windowing is performed **within each subject** to preserve temporal structure and avoid leakage. The effective **sampling rate is estimated from timestamps** to translate time-based window definitions (seconds) into sample indices in a data-driven way.

Each window is assigned a single activity label using a **majority vote** over the samples it contains. To reduce label noise near activity transitions, we apply a **label purity threshold of 0.8** (a common choice in HAR) and **discard windows below this threshold**, focusing the model on learning from **steady-state activities** rather than ambiguous transition regions.

```
Estimated fs: 100 Hz | window: 500 samples (5.0s) | step: 250 samples (50%
overlap)

Windows: (7645, 500, 17) | Labels: (7645,) | Groups: (7645,)

            n_windows  kept_fraction
subject_id
101               983       0.984970
102              1037       0.985741
103               685       0.984195
104               912       0.987013
105              1075       0.988051
106               984       0.984985
107               913       0.981720
108              1032       0.985673
109                24       1.000000
```



5. Feature extraction

In this section, we convert each windowed wrist IMU signal into a **fixed-length feature vector** suitable for classical machine learning models.

For each window and each signal, we compute the following **simple time-domain features**:

- mean
- standard deviation
- median
- minimum
- maximum

- interquartile range (IQR)

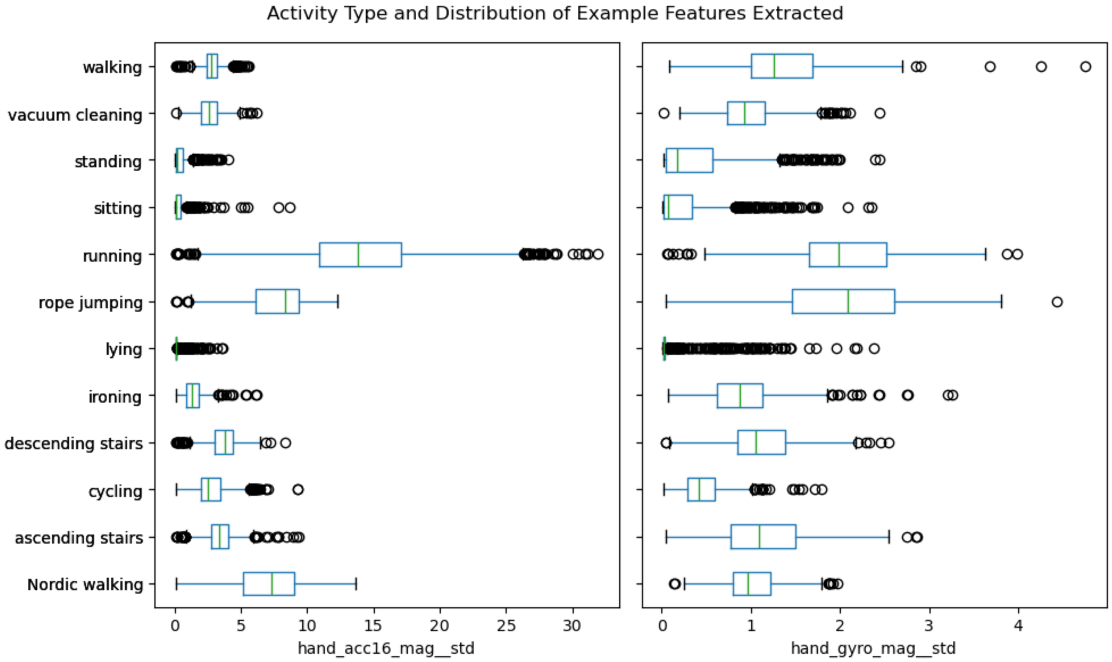
- root mean square (RMS)

These statistics capture signal level, variability, range, and overall energy within the window.

This feature-based representation is a **standard approach in wearable activity recognition** for classical models such as logistic regression and gradient boosting. More complex energy-style or frequency-domain features are intentionally omitted here to keep the notebook compact and focused.

```
Feature matrix: (7645, 119)
n_features: 119
```

As a lightweight sanity check, we inspect the **univariate distributions** of a small number of representative features. This helps verify that the extracted features have sensible ranges and capture differences across activities, without performing extensive exploratory analysis.



6. Modeling & subject-wise evaluation

In this section, we train and evaluate classical activity recognition models using the extracted window-level features, with a validation protocol that reflects **generalization to unseen users**.

We use **GroupKFold cross-validation**, grouping by `subject_id`, to ensure that windows from the same subject never appear in both training and test folds. This avoids subject-level leakage and mirrors real wearable deployment scenarios.

We evaluate two model families: - **Logistic Regression (LR)** as a simple, interpretable baseline (with feature standardization). - **Histogram-based Gradient Boosting (HGB)** as a stronger classical model for tabular data.

For each model, we compare performance using: - the **original feature space**, and - a **PCA-compressed feature space**, where PCA retains **90% of the variance** and is fit **within each training fold** via a pipeline to avoid leakage.

The PCA-based evaluation is included **to relate model performance to the upcoming decision boundary visualizations in PCA space**, rather than to mimic a real deployment setup.

We report **macro-F1** (primary metric) and **balanced accuracy** (secondary metric), summarized as mean ± standard deviation across folds.

The results of this section provide a quantitative basis for comparing models and feature representations, and set the stage for the interpretability visualizations in the final section.

```
CV: LR: 100%|
                                                  | 5/5
[00:00<00:00,  5.92it/s]
CV: LR+PCA(90%): 100%|
                                                  | 5/5
[00:00<00:00,  6.82it/s]
CV: HGB: 100%|
                                                  | 5/5
[00:39<00:00,  7.83s/it]
CV: HGB+PCA(90%): 100%|
                                                  | 5/5
[00:42<00:00,  8.60s/it]
```

```
Model performance (GroupKFold, mean ± std)


          model  macro_f1_mean  macro_f1_std  bal_acc_mean  bal_acc_std
0            LR       0.711154      0.118526      0.760811     0.120261
3  HGB+PCA(90%)       0.702619      0.066123      0.757207     0.069615
1   LR+PCA(90%)       0.682259      0.120925      0.736321     0.108132
2           HGB       0.658061      0.181828      0.713408     0.147955
```

```
Test-fold label counts (5 folds)

   fold  lying  sitting  standing  walking  running  cycling  Nordic walking  \
0     0    189      178       201      254      101      199             232
1     1    200      184       181      189      174      174             186
2     2     87      114        81      115        0        0               0
3     3    185      207       186      254       98      186             213
4     4    101       47       101      134       14       89             114

   ascending stairs  descending stairs  vacuum cleaning  ironing  rope jumping
0               111                 95              178      245            86
1               112                101              173      243            50
2                39                 58               80      111            24
3               119                104              176      230            29
4                68                 44               85      116             0
```

7. Results & error analysis

We summarize the modeling results using a small set of diagnostic plots focused on **performance stability** and **error structure**.

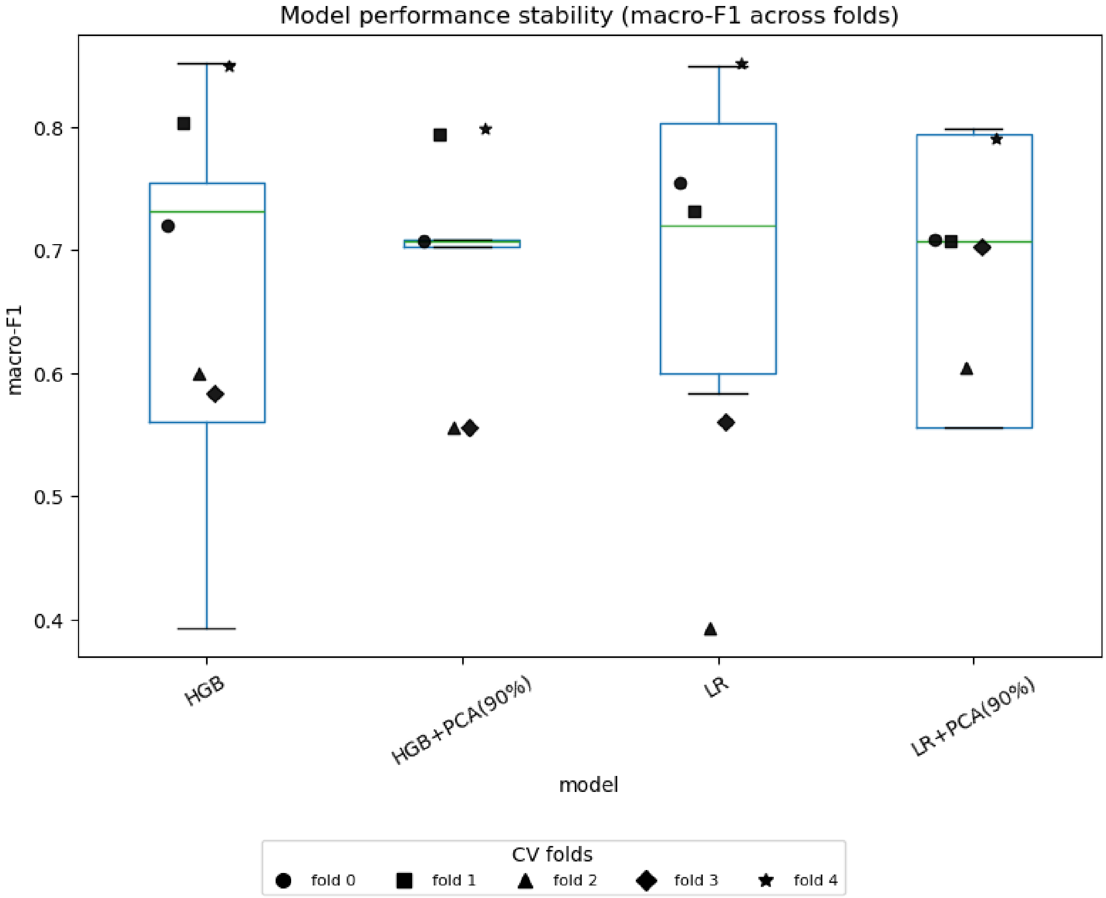
First, we compare models using their **fold-wise macro-F1 distributions**, which highlights both average performance and variability across subject-wise folds.

We then inspect the **aggregated confusion matrix** for the best-performing model to understand common confusions between activities.

Finally, we visualize **per-subject macro-F1 variability** for the best model to assess how performance differs across users.

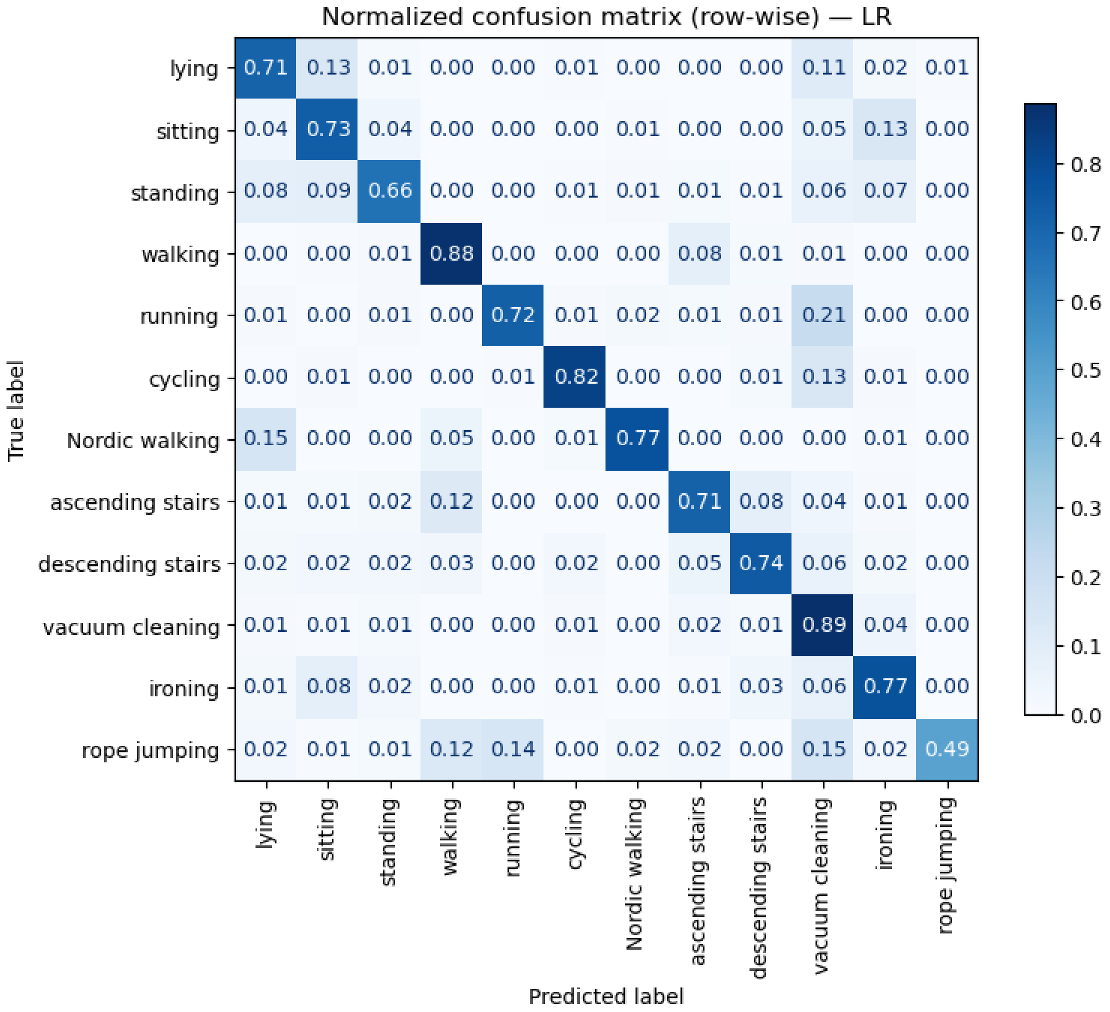
7.1 Model performance stability

We first compare models using their **fold-wise macro-F1 distributions** across subject-wise cross-validation splits. This visualization highlights not only average performance, but also **stability across folds**, which is important when evaluating generalization to unseen users.



7.2 Aggregated confusion matrix

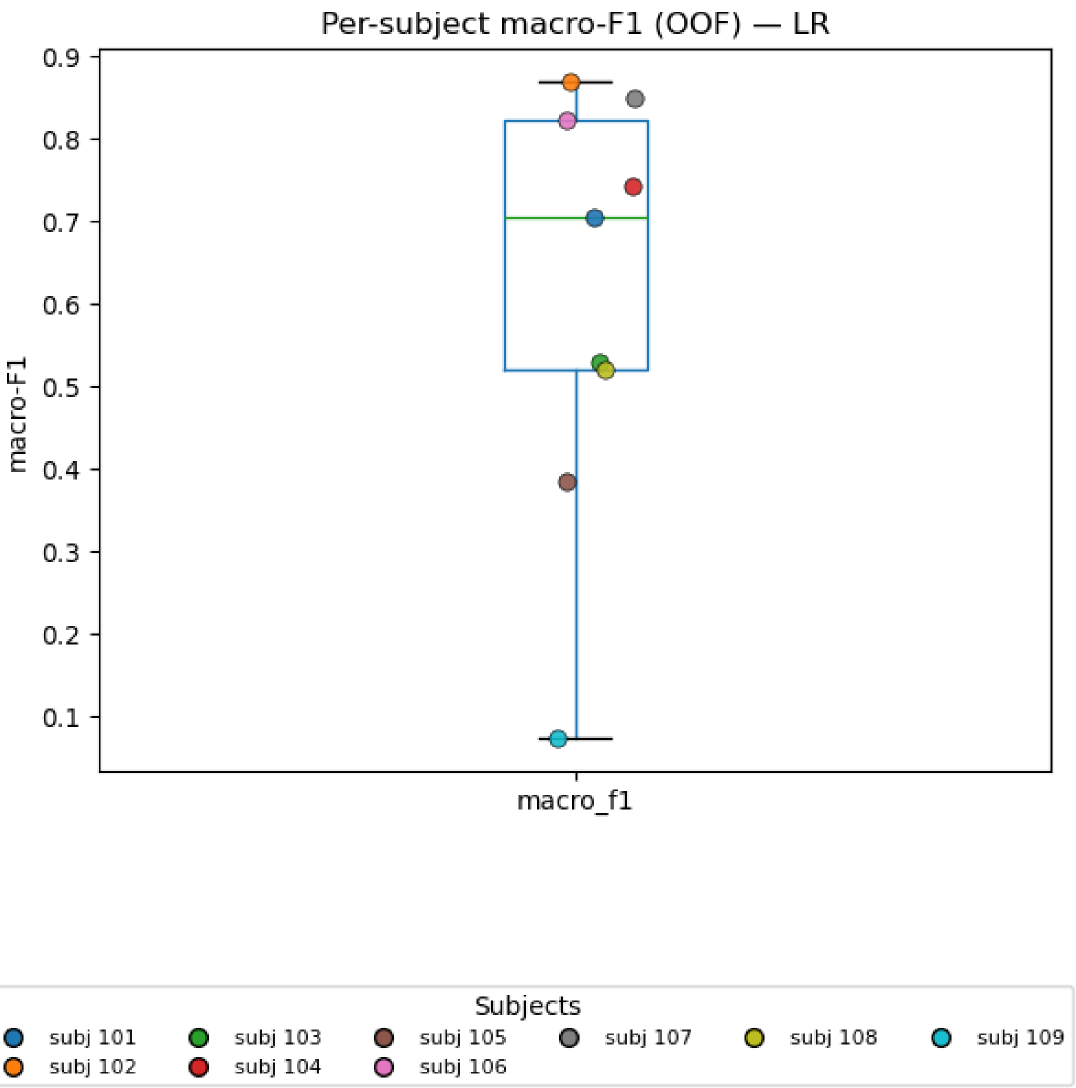
We inspect the **aggregated confusion matrix** for the best-performing model (based on mean macro-F1). This helps identify systematic confusions between activity classes and provides insight into common failure modes.



	lying	sitting	standing	walking	running	cycling	Nordic walking	ascending stairs	descending stairs	vacuum cleaning	ironing	rope jumping
lying	0.71	0.13	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.11	0.02	0.01
sitting	0.04	0.73	0.04	0.00	0.00	0.00	0.01	0.00	0.00	0.05	0.13	0.00
standing	0.08	0.09	0.66	0.00	0.00	0.01	0.01	0.01	0.01	0.06	0.07	0.00
walking	0.00	0.00	0.01	0.88	0.00	0.00	0.00	0.08	0.01	0.01	0.00	0.00
running	0.01	0.00	0.01	0.00	0.72	0.01	0.02	0.01	0.01	0.21	0.00	0.00
cycling	0.00	0.01	0.00	0.00	0.01	0.82	0.00	0.00	0.01	0.13	0.01	0.00
Nordic walking	0.15	0.00	0.00	0.05	0.00	0.01	0.77	0.00	0.00	0.00	0.01	0.00
ascending stairs	0.01	0.01	0.02	0.12	0.00	0.00	0.00	0.71	0.08	0.04	0.01	0.00
descending stairs	0.02	0.02	0.02	0.03	0.00	0.02	0.00	0.05	0.74	0.06	0.02	0.00
vacuum cleaning	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.02	0.01	0.89	0.04	0.00
ironing	0.01	0.08	0.02	0.00	0.00	0.01	0.00	0.01	0.03	0.06	0.77	0.00
rope jumping	0.02	0.01	0.01	0.12	0.14	0.00	0.02	0.02	0.00	0.15	0.02	0.49

7.3 Per-subject performance variability

Finally, we analyze **per-subject macro-F1 performance** for the best model. This highlights how recognition accuracy varies across individuals, an important consideration for wearable deployment scenarios.



7.4 Results summary

Overall model comparison (GroupKFold, subject-wise): - **Best mean performance: LR (original features)** achieved **macro-F1 = 0.71 ± 0.12** and **balanced accuracy = 0.76 ± 0.12**. - **Most stable across folds: HGB+PCA(90%)** was close in mean performance (**macro-F1 = 0.70 ± 0.07**, **bal-acc = 0.76 ± 0.07**) with visibly tighter variability than the other variants. - **PCA impact:** PCA slightly reduced LR performance on average (LR+PCA macro-F1 0.68), while HGB benefited from PCA in stability (HGB+PCA vs HGB).

Error structure (normalized confusion matrix, LR): - Several activities show strong recall (row-wise): e.g., **walking (~0.88)**, **vacuum cleaning (~0.89)**, **cycling (~0.82)**. - The hardest class in this subset is **rope jumping** (~**0.49** recall), with confusions spread across high-motion classes (notably walking/running/vacuum cleaning). - Some expected confusions appear among semantically/kinematically similar classes: - **standing** mixes with **lying/sitting**. - **running** shows noticeable confusion with **vacuum cleaning** in this split.

Per-subject variability (OOF macro-F1, LR): - Performance varies substantially across users: from ~**0.87 (best subject)** down to ~**0.07 (worst subject)**. - This highlights that while the global model generalizes reasonably on average, **user-level differences and intra-subject physiological variability** are a major source of uncertainty, motivating **per-user calibration or personalization** in practical wearable deployments.

8. Model interpretability in PCA space

In this final section, we build intuition about how the trained models separate activity classes by visualizing their **decision regions in PCA space**.

After cross-validation is complete, we refit the PCA-based pipelines **once on the full dataset**, using the same default settings as in Section 6. This refit is performed purely for **interpretability and visualization**, not for estimating performance.

Because the PCA-based models operate in a **higher-dimensional PCA space** (retaining 90% of variance), but decision boundary plots can only be shown in 2D, we visualize a **2D slice** of the full model in the **PC1–PC2 plane**:

- We create a grid in the **PC1–PC2** plane.
- We embed these grid points into the full PCA space by setting the remaining PCs (PC3 … PCk) to **0**, corresponding to their mean values in centered PCA coordinates.
- We map these points back to the original feature space via inverse transforms and obtain predictions from the **original trained model**.

This approach follows standard practice in applied machine learning when visualizing high-dimensional classifiers: PCA components are zero-centered by construction (see e.g. *Jolliffe & Cadima, 2016, "Principal Component Analysis: A Review and Recent Developments"*), so fixing higher components at zero corresponds to holding them at their average values. The inverse PCA transformation used here is the same mechanism described in the scikit-learn PCA documentation and textbooks on linear dimensionality reduction.

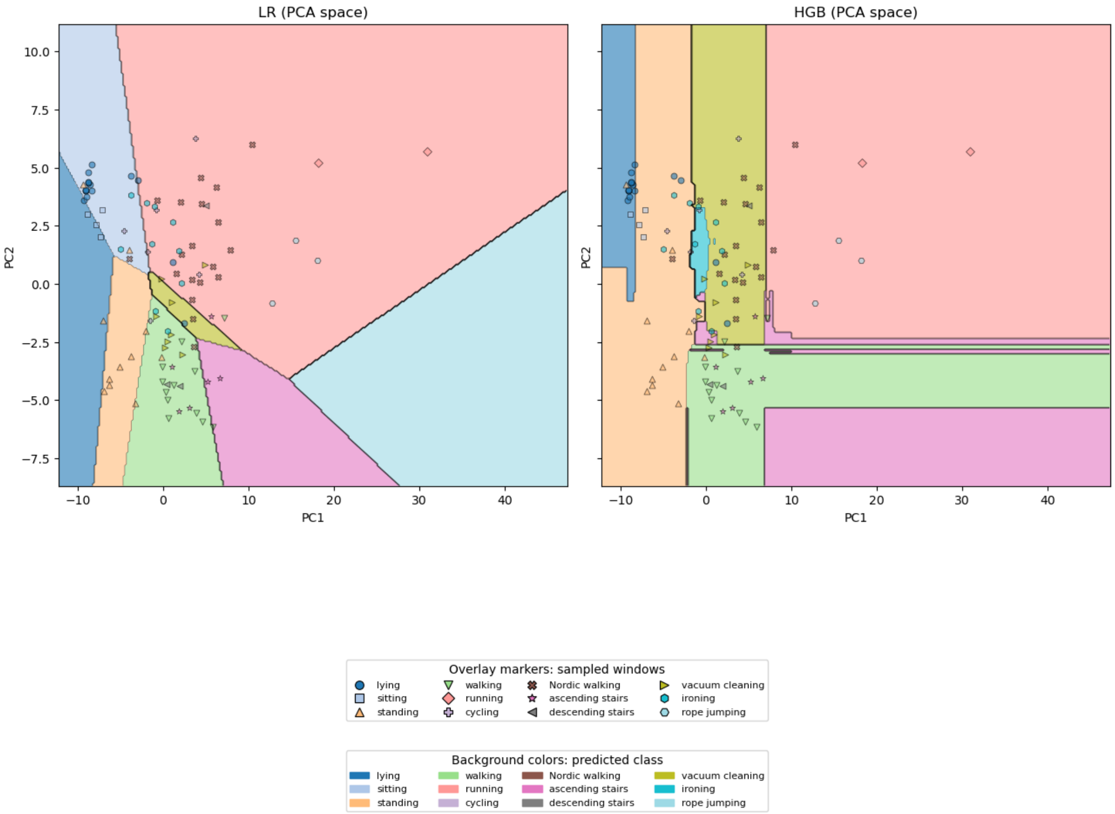
The resulting decision regions are therefore **faithful to the full PCA-based model**, but should be interpreted as model behavior along PC1–PC2 **with all other PCA directions held constant**. This kind of 2D slicing is widely used for interpretability and visualization, while performance is always evaluated in the full feature space or a sufficiently rich reduced space (e.g. 90–95% variance PCA), rather than in only two components.

To aid interpretation, we overlay: - a random global subsample of windows

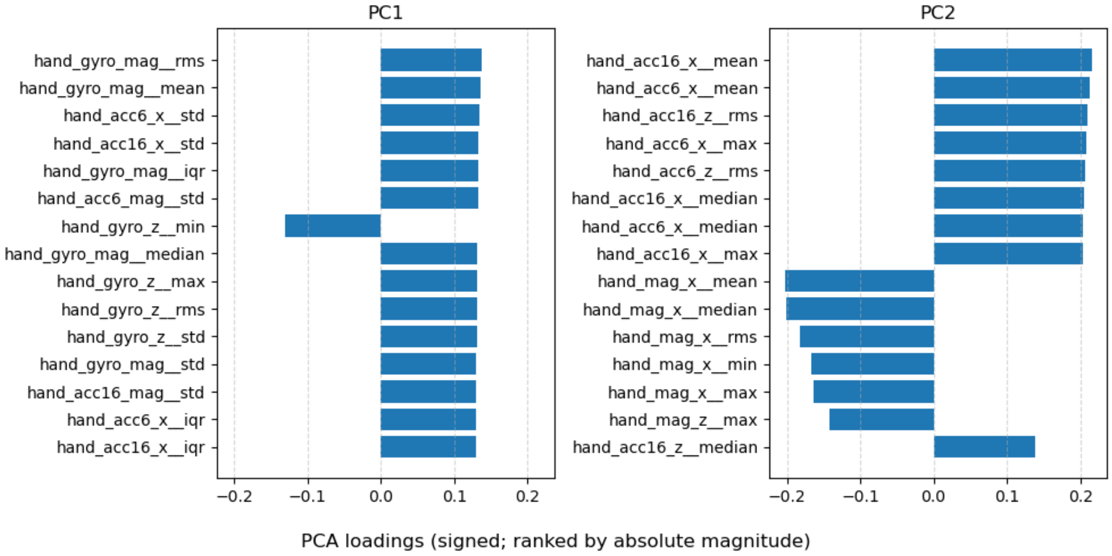
Finally, we inspect the **PC1 and PC2 loadings** (top absolute contributors of each indepandantly) to see which original features most strongly drive the dominant PCA direction used in the visualization.

8.1 Global overlay of random subsample of windows

```
PCA components kept: 17
```



8.2 PCA loadings



8.3 Comments

The PCA-based visualizations provide qualitative insight into how the models structure activity separation, without serving as a performance assessment tool.

- **PC1–PC2 structure:**
  The first two principal components reveal some organization of activities.

- **Model behavior differences:**
  The Logistic Regression decision regions are smooth and globally linear in PCA space, while the Gradient Boosting model forms sharper, axis-aligned regions and stronger nonlinearity observed.

- **Overlap and ambiguity:**
  Significant overlap remains between related activities.

- **PCA loadings:**
  PC1 is dominated by **gyroscope magnitude and axis-specific statistics** (mean, RMS, IQR, std), with additional contribution from accelerometer magnitude features. This indicates that PC1 primarily captures **overall wrist motion intensity**, combining rotational and translational energy.
  PC2 shows strong contributions from **accelerometer axis statistics** (especially x/z mean, RMS, max, median), contrasted by **magnetometer features** with large negative loadings. This suggests PC2 separates **directional linear motion** from **orientation-related or heading-stability cues**.

Overall, these visualizations support the quantitative results: the models learn reasonable global structure, but **class overlap and subject-specific variability** remain fundamental challenges—motivating personalization or temporal modeling in more advanced setups.