# Paper ID : 1024 Classical machine learning and deep neural network ensemble model for GPS-based activity recognition

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## Dataset

### Description

Target : Recognize 8 modes of locomotion Still, Walk, Run, Bike, Car, Bus, Train, Subway

Dataset : GPS, WiFi, GSM cell tower time series data

Dataset split :

- Train : 59 days, user 1
- Valid : 4 days, mixture of user2 and user3
- Test : 39 days, mixture of user2 and user3

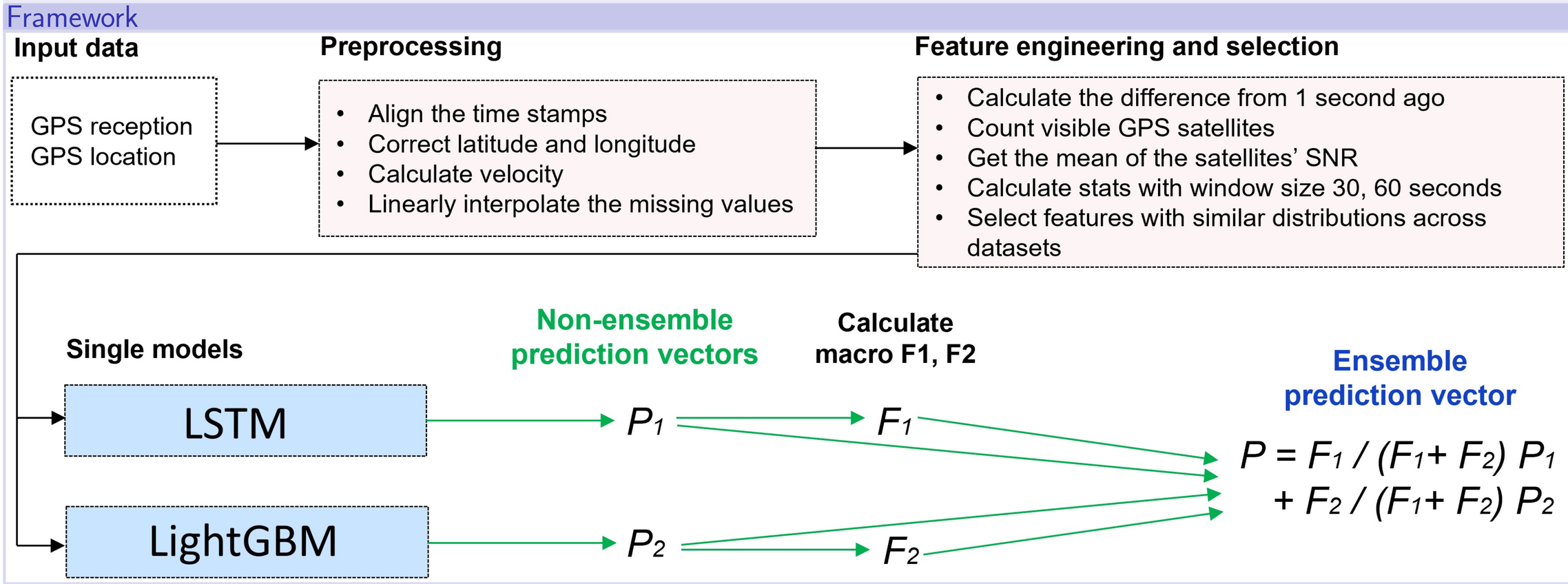
### Sensor data format

| Modality | Data format |
|---|---|
| GPS reception | satellites ID, SNR, Azimuth, Elevation |
| GPS location | Accuracy, Latitude, Longitude, Altitude |
| WiFi reception | BSSID, SSID, Frequency, Capabilities |
| Cell tower | type of cell, area code and signal level, etc. |

- Portions of the sensor data are often missing due to satellite reception status, hardware glitches or human errors, among others, and
- Sampling rate is asynchronous, albeit assumed to be roughly 1Hz.

## Our approach

### Framework




### Ensemble modeling

- LightGBM : lambda_l1 = 0, lambda_l2 = 0, num_leaves = 9, feature_fraction = 0.7, bagging_fraction = 1.0, bagging_freq = 0, min_child_samples = 20
- LSTM : hidden_size = 250, num_of_layers = 2
- The weighted average ensemble method of two models with high macro F1 score in these three models. That is, if the prediction probability vector of model $i(=1,2,3)$ is $\boldsymbol{p}_i$ and its macro F1 score is $F_i$, and asuuming $F_1 > F_2 > F_3$. Then the prediction probability vector of the ensemble model is $\boldsymbol{P} = \frac{F_1}{(F_1+F_2)}\boldsymbol{p}_1 + \frac{F_2}{(F_1+F_2)}\boldsymbol{p}_2$, and the label corresponding to the element that maximizes this vector $\boldsymbol{P}$ is used as the final recognition label.

## Experimental Result

Table: macro F1 score of base models for train dataset

| Base model | macro F1 | w/o kalman-smoother | w/o feature selection |
|---|---|---|---|
| Random Forest | 0.790 | 0.641 | 0.744 |
| LightGBM | 0.886 | 0.850 | 0.801 |
| LSTM | 0.890 | 0.822 | 0.834 |

Table: macro F1 score of base models for validation dataset

| Base model | macro F1 | w/o kalman-smoother | w/o feature selection |
|---|---|---|---|
| Random Forest | 0.688 | 0.602 | 0.552 |
| LightGBM | **0.824** | 0.720 | 0.602 |
| LSTM | **0.867** | 0.797 | 0.670 |

Table: Ensemble model score

| Dataset | macro F1 | macro precision | macro recall |
|---|---|---|---|
| train | 0.901 | 0.898 | 0.943 |
| validation | **0.887** | 0.875 | 0.933 |

## Confusion matrix

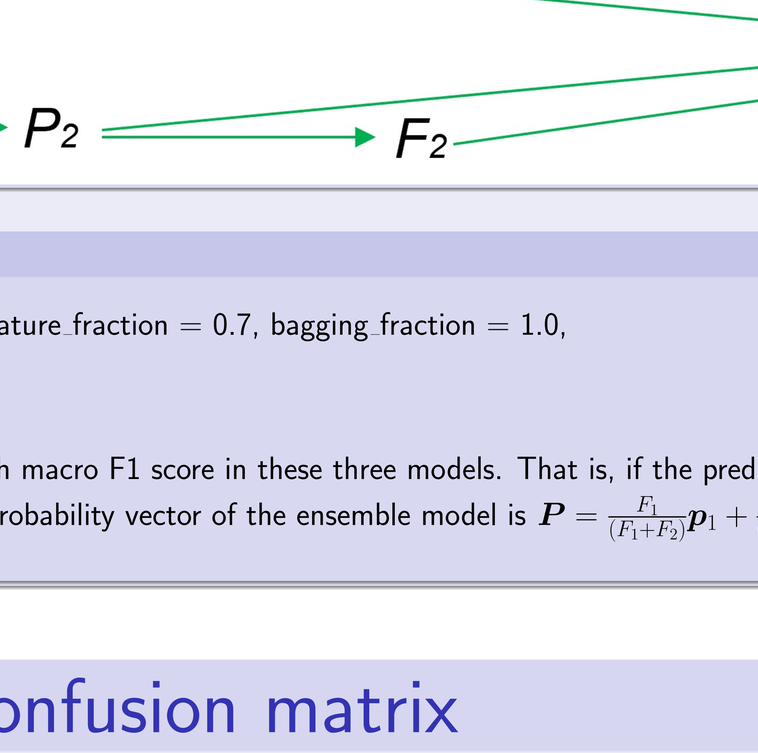



Figure: Confusion matrix of ensemble model for validation dataset

## Conclusion

- Macro F1 score is improved by correcting the GPS location with kalman-smoother in the preprocessing and focusing on the features with similar distributions in the train and other dataset.
- Ensemble model based on traditional machine learning and deep neural network model, and has higher macro F1 score than each single model.
- There remains a big issue of mispredicting other than "Subway" (especially "Still" and "Train").
- This is due to the unstable state of GPS satellites other than "Subway", so we assume that we will improve in the future by using WiFi reception and Cell tower reception data that we did not use this time.

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