# Final report on light curves classification

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## 1.Introduction

To study astronomical sources from our universe, astronomers need facilities like telescopes to collect and analyze lights or radiations. The Large Synoptic Survey Telescope (LSST) is a powerful telescope that will start its main survey in 2022. It is so revolutionary as it collect much more astronomical data than other telescopes. For example, each and every week LSST will find more sources than Hubble has ever seen in its entire 28+ year life.

Roughly speaking, LSST can “see” astrophysical sources in the night sky that change in brightness over time, and these time-series of brightness (also called “light curves”) will be recorded. Our dataset is based on a SIMULATION of the light curves that LSST can expect to collect.

In this project, our goal is to classify astronomical sources into different classes according to their light curves.

## 2.Exploratory data analysis

### Data Information

```
library(ggplot2)
library(dplyr)
library(forcats)
library(ggpubr)
```

```
load("../Data/project_data.Rdata")
head(train_meta_data)
```

```
##   object_id         ra       decl    gal_l     gal_b ddf hostgal_specz
## 1       615 349.046051 -61.943836 320.7965 -51.75371   1        0.0000
## 2       713  53.085938 -27.784405 223.5255 -54.46075   1        1.8181
## 3       730  33.574219  -6.579593 170.4556 -61.54822   1        0.2320
## 4       745   0.189873 -45.586655 328.2545 -68.96930   1        0.3037
## 5      1124 352.711273 -63.823658 316.9223 -51.05940   1        0.1934
## 6      1227  35.683594  -5.379379 171.9929 -59.25350   1        0.0000
##   hostgal_photoz hostgal_photoz_err distmod mwebv target
## 1         0.0000             0.0000     NaN 0.017     92
## 2         1.6267             0.2552 45.4063 0.007     88
## 3         0.2262             0.0157 40.2561 0.021     42
## 4         0.2813             1.1523 40.7951 0.007     90
## 5         0.2415             0.0176 40.4166 0.024     90
## 6         0.0000             0.0000     NaN 0.020     65
```

```
head(train_data)
```

```
##   object_id      mjd passband       flux  flux_err detected
## 1       615 59750.42        2  -544.8103  3.622952        1
## 2       615 59750.43        1  -816.4343  5.553370        1
## 3       615 59750.44        3  -471.3855  3.801213        1
## 4       615 59750.44        4  -388.9850 11.395031        1
## 5       615 59752.41        2  -681.8589  4.041204        1
## 6       615 59752.41        1 -1061.4570  6.472994        1
```

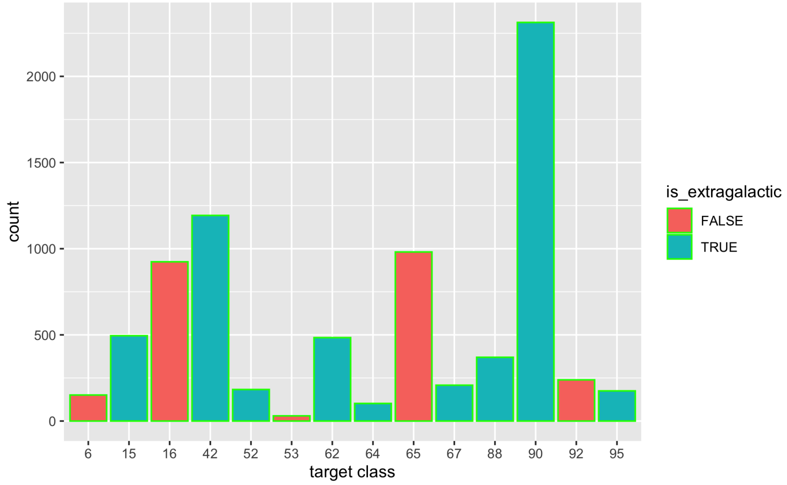
So here we have 1421705 training data, each corresponding to a observation, and there are 7848 astronomical sources in total. Some important attributes are summarized below:

- In `train_data`:
  - `object_id`: unique index of astronomical source.
  - `mjd`: the time in Modified Julian Date (MJD) of the observation.
  - `flux`: the "brightness" of this source at this time.
  - `passband`: six integers from 0 to 5. Flux can be measured from these six filters.
- In `train_meta_data`:
  - `target`: the class of the astronomical source and there is 14 classes in total.
  - `ra,decl`: sky coordinates, represent the direction of the source.
  - `hostgal_specz`: the spectroscopic redshift of the source, represents the distance between us and the source. This is usually missing in real data, so can not be used as a feature.
  - `hostgal_photoz,hostgal_photoz_err`: estimated spectroscopic redshift and its error.

### Meta data visualization

```
train_meta_data = train_meta_data %>%
        mutate(is_extragalactic=as.logical(hostgal_specz),
               object_id =as.factor(object_id),target=as.factor(target))
id2class = train_meta_data$target
names(id2class) = train_meta_data$object_id
train_data = train_data %>%
  mutate(object_id =as.factor(object_id),
        passband=as.factor(passband),target=id2class[object_id])
```

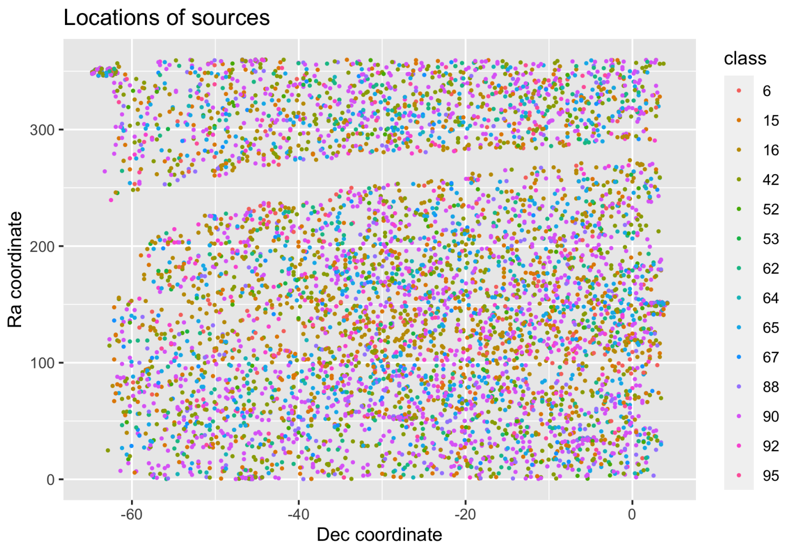
```
train_meta_data %>% ggplot() +
  geom_bar(aes(x=target,fill=is_extragalactic),stat="count",colour="green")+
  labs(x="target class",y="count")

ggsave("./Images/img1.png")
```



We have 14 classes and the class distribution in the training set is imbalanced. There are more than 2000 sources in class 90 but only 30 sources in class 53.

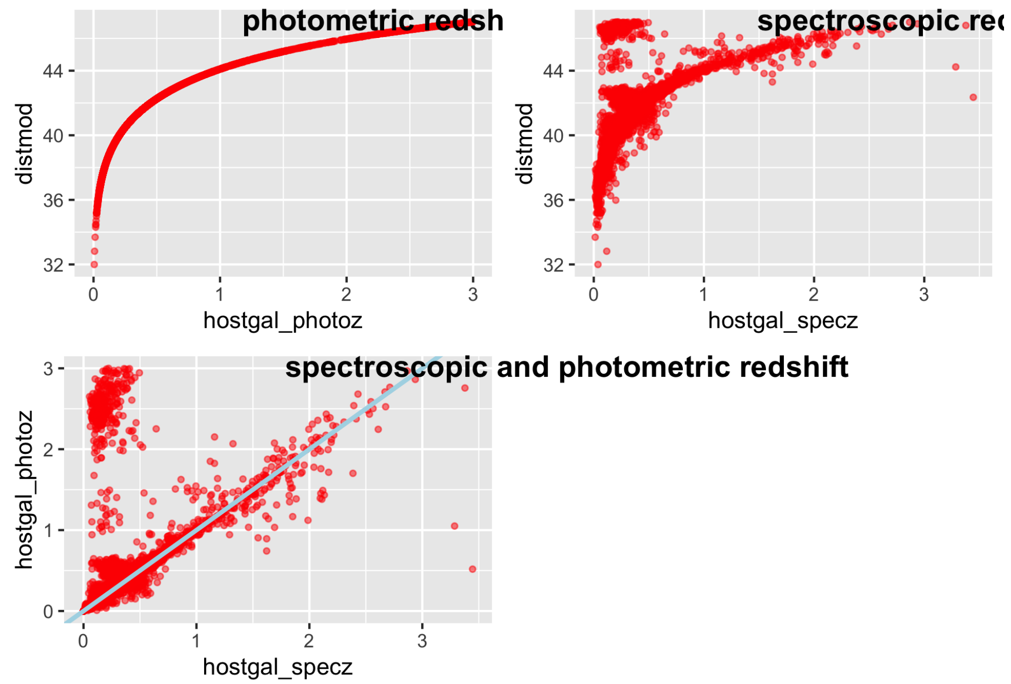
Also, there is no overlap at all between the galactic and extragalactic sources in the training set. So we may train different models for these two sets of sources.

```
train_meta_data %>% ggplot()+geom_point(aes(x=decl,y=ra,color=target),size = 0.5)+
  labs(x="Dec coordinate",y="Ra coordinate",color="class",title="Locations of sources")
ggsave("./Images/img2.png")
```



It seems that the class distribution is not uniform in our coordinate system. Thus the coordinates may help us do classification.

```
p1 = ggplot(train_meta_data)+geom_point(aes(x=hostgal_photoz,y=distmod ),color="red",size=1,alpha=0.5)
p2 = ggplot(train_meta_data)+geom_point(aes(x=hostgal_specz,y=distmod ),color="red",size=1,alpha=0.5)
p3 = ggplot(train_meta_data)+
  geom_point(aes(x=hostgal_specz,y=hostgal_photoz),color="red",size=1,alpha=0.5)+
  geom_abline(aes(slope=1,intercept=0),color="lightblue",size=1)

figure <- ggarrange(p1, p2,p3,
                    labels = c("photometric redshift and distmod",
                               "spectroscopic redshift and distmod",
                               "spectroscopic and photometric redshift"),
                    ncol = 2, nrow = 2)
ggsave("./Images/img3.png")
```

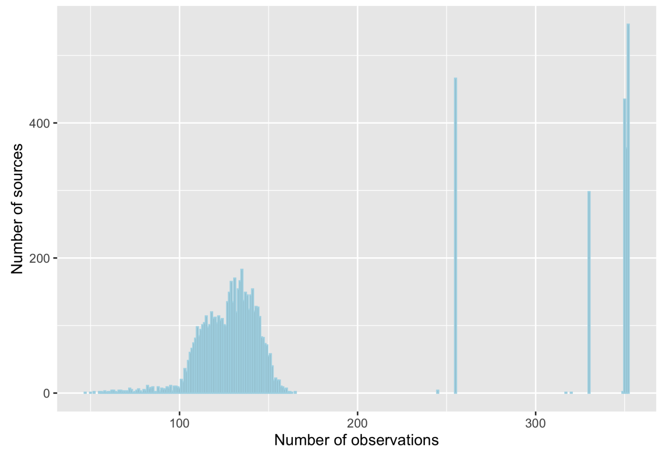


To determine the location of a source, we need both direction and distance. However, we can see attribute `distmod` is just a transformed `hostgal_photoz`, which is the estimated “distance” and can be strongly biased from the real `hostgal_specz`.

### Training data visualization

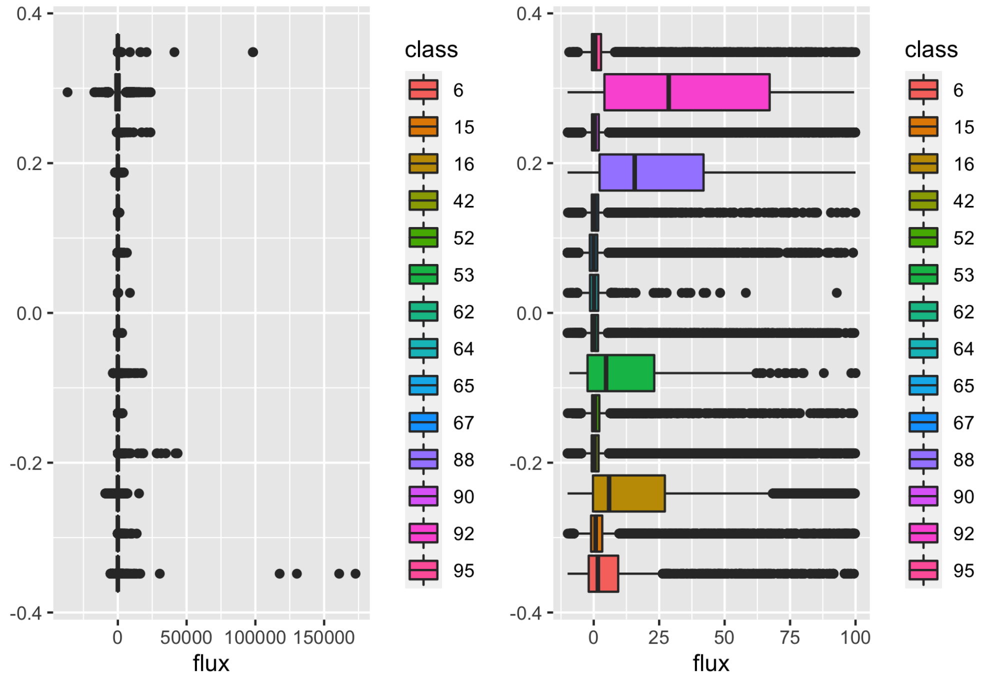
We notice that each source can have different number of observations and observations are at different time points. In detail, some sources have more than 500 obverservitions and some sources only have less than 100 observations. Thus data preprocessing is asked.

```
train_data %>% count(object_id) %>%
  ggplot(aes(n))+geom_bar(stat="count",color="lightblue")+
  labs(x="Number of observations",y="Number of sources")
ggsave("./Images/img4.png")
```



Here, we pick up one source for each class and we draw a box plot(left) of flux for the passband 1. As there are too many outliers, we zoom in this box plot(right).

```
plot_data = train_data %>% filter(passband==1) %>% group_by(target)
p1 = plot_data %>%  ggplot() + geom_boxplot(aes(x=flux,fill=target)) + labs(x="flux",fill="class")

p2 = plot_data %>% ggplot() + geom_boxplot(aes(x=flux,fill=target)) + labs(x="flux",fill="class") +scale
figure <- ggarrange(p1, p2,ncol = 2, nrow = 1)
ggsave("./Images/img5.png")
```



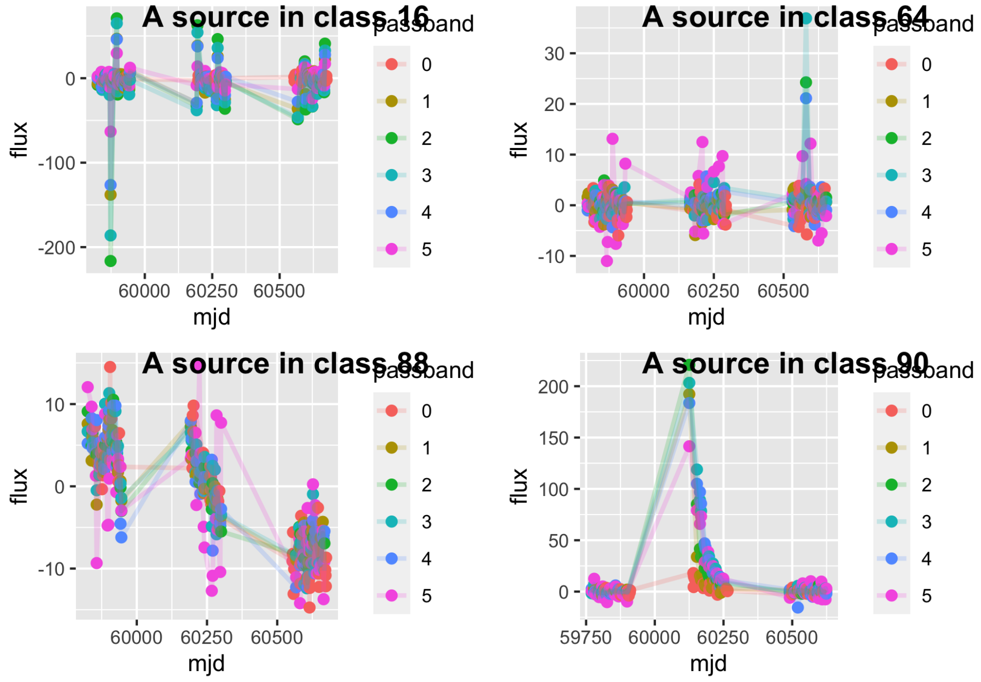
Basically, there are two type of classes:

- classes like class 92 with large interquartile range and less outliers. They may be stars like binary systems.
- classes like class 6 with small interquartile range and many outliers. They may be stars like supernovas.

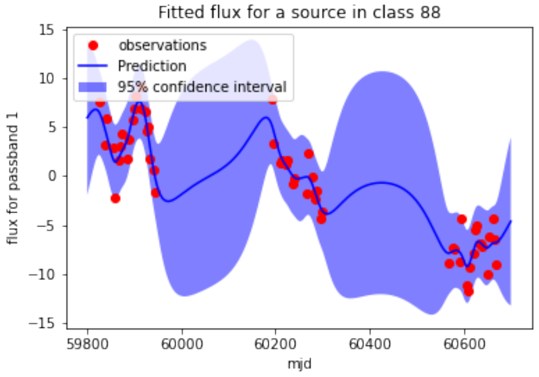
Here we show the the light curves for some sources:

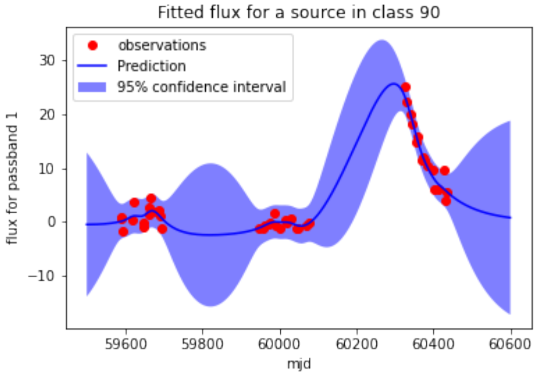
```
index = which(train_meta_data$target==16)[1]
object = as.integer(train_meta_data$object_id[index])
object = train_data[which(as.integer(train_data$object_id)==as.integer(object)),]
p1 = object%>% ggplot() + geom_point(aes(x=mjd,y=flux,color=passband),size=2) + geom_line(aes(x=mjd,y=fl
#################
index = which(train_meta_data$target==64)[1]
object = as.integer(train_meta_data$object_id[index])
object = train_data[which(as.integer(train_data$object_id)==as.integer(object)),]
p2 = object %>% ggplot() + geom_point(aes(x=mjd,y=flux,color=passband),size=2) + geom_line(aes(x=mjd,y=
##################
index = which(train_meta_data$target==88)[1]
object = as.integer(train_meta_data$object_id[index])
object = train_data[which(as.integer(train_data$object_id)==as.integer(object)),]
p3 = object %>% ggplot() + geom_point(aes(x=mjd,y=flux,color=passband),size=2) + geom_line(aes(x=mjd,y=
##################
index = which(train_meta_data$target==90)[1]
object = as.integer(train_meta_data$object_id[index])
object = train_data[which(as.integer(train_data$object_id)==as.integer(object)),]
```

```
p4 = object %>% ggplot() + geom_point(aes(x=mjd,y=flux,color=passband),size=2) + geom_line(aes(x=mjd,y=


figure <- ggarrange(p1, p2,p3,p4,
                    labels = c("A source in class 16", "A source in class 64","A source in class 88", "
ggsave("./Images/img6.png")
```



It is natural to fit light curves with time series or Gaussian processes as they change over time. For example, we can fit the flux for passband 1 with Gaussian process:





## 3.Gaussian process modeling and data augmentation

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Now we denote observation time `mjd` by $t$ and brightness `flux` by $f$. For the `passband`, the flux value in a passband is actually a "weighted average" of fluxes from many wavelengths. The information for passband can be found in some additional source. We will later consider passbands as corresponding weighted average wavelengths. That is, passband 0 to 5 stands for wavelengths $l_0$ to $l_5$.

As our data are actually time series, we need to transfer them to finite-dimensional covariates.

The method we use is **Gaussian process regression**.

Notice flux between different passbands(wavelengthes) are obviously correlated, thus we define a Gaussian process a two-dimensional time-wavelength space:

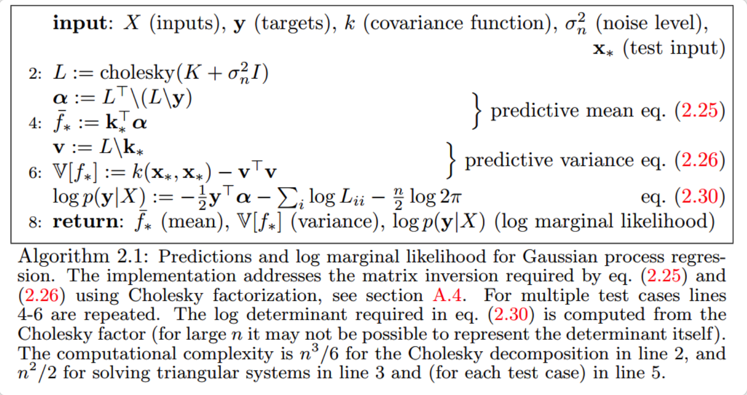
$$f(\mathbf{x}) \sim \mathcal{GP}\left(0, k\left(\mathbf{x}, \mathbf{x}'\right)\right), \quad \mathbf{x} = (t, l), \mathbf{x}' = (t', l')$$

and the kernel $k\left(\mathbf{x}, \mathbf{x}'\right)$ is chosen to be Matern covariance kernel with smoothness 1.5:

$$k\left(\mathbf{x}, \mathbf{x}'\right) = \sigma^2 (1 + d) \exp(-d) + \tau^2 1_{\{d=0\}}, \quad d = \sqrt{\left(\frac{t - t'}{\rho_t}\right)^2 + \left(\frac{l - l'}{\rho_l}\right)^2}$$

As we only have 6 passbands, it is not likely to get a good estimation for $\rho_l$. We fix $\rho_l = 600(nm)$ and thus model parameters are $\theta = \{\sigma^2, \tau^2, \rho_t\}$.

The parameters estimation is done by MLE, more precisely, see algorithm 2.1 from this book.



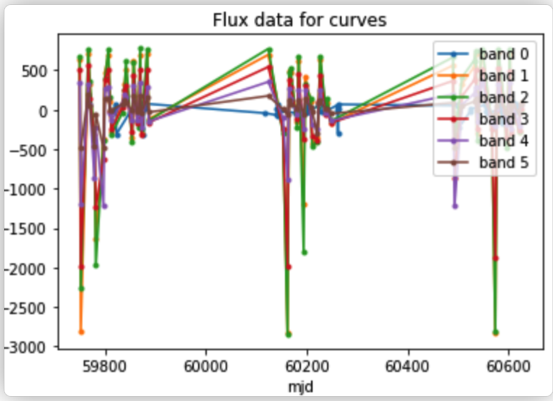
```
    input: $X$ (inputs), $\mathbf{y}$ (targets), $k$ (covariance function), $\sigma_n^2$ (noise level),
                                                                        $\mathbf{x}_*$ (test input)
2:  $L := \text{cholesky}(K + \sigma_n^2 I)$
    $\boldsymbol{\alpha} := L^\top \backslash (L \backslash \mathbf{y})$      } predictive mean eq. (2.25)
4:  $\bar{f}_* := \mathbf{k}_*^\top \boldsymbol{\alpha}$
    $\mathbf{v} := L \backslash \mathbf{k}_*$                                 } predictive variance eq. (2.26)
6:  $\mathbb{V}[f_*] := k(\mathbf{x}_*, \mathbf{x}_*) - \mathbf{v}^\top \mathbf{v}$
    $\log p(\mathbf{y}|X) := -\frac{1}{2}\mathbf{y}^\top \boldsymbol{\alpha} - \sum_i \log L_{ii} - \frac{n}{2} \log 2\pi$      eq. (2.30)
8:  return: $\bar{f}_*$ (mean), $\mathbb{V}[f_*]$ (variance), $\log p(\mathbf{y}|X)$ (log marginal likelihood)
```

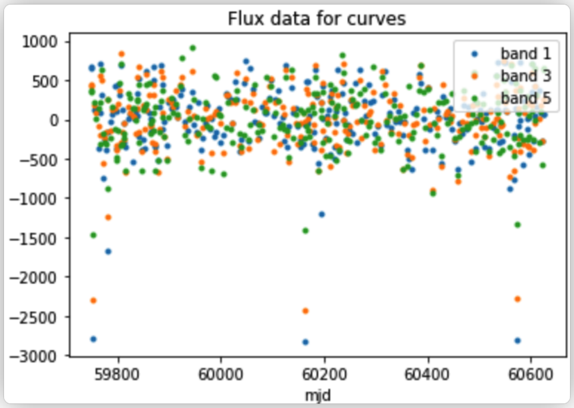
Algorithm 2.1: Predictions and log marginal likelihood for Gaussian process regression. The implementation addresses the matrix inversion required by eq. (2.25) and (2.26) using Cholesky factorization, see section A.4. For multiple test cases lines 4-6 are repeated. The log determinant required in eq. (2.30) is computed from the Cholesky factor (for large $n$ it may not be possible to represent the determinant itself). The computational complexity is $n^3/6$ for the Cholesky decomposition in line 2, and $n^2/2$ for solving triangular systems in line 3 and (for each test case) in line 5.

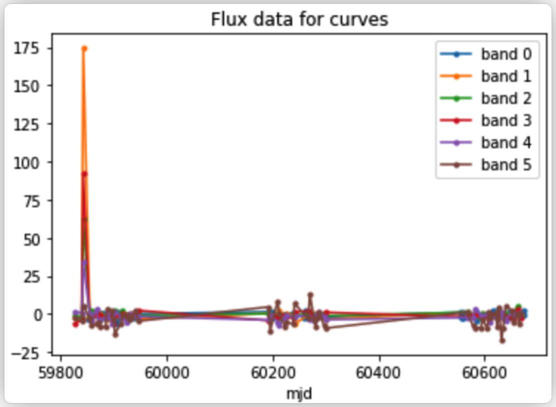
After this, we do data augmentation by sampling from the posterior distribution at certain passbands and time points.

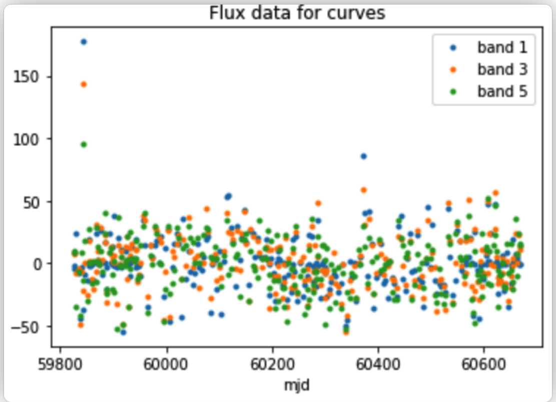
- We only do this for passbands 1,3,5
- We choose about 300 time points for each sampled curve.
- On average, 14 samples are drawn for each original data. In detail, for a curve in class $i$, we generate $n_i$ curves by sampling from the posterior distribution, where $n_i = \text{floor}(400/N_i)$ and $N_i$ is the number of original sources in class $i$. That is, in augmented data set, **each class has approximately the same number of light curves**.

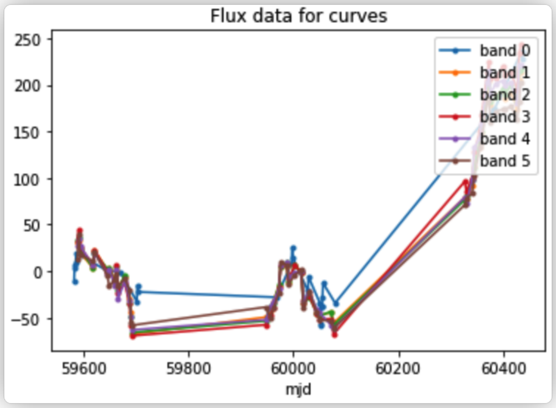
Here are three examples of original curves(left) and sampled curves(right):

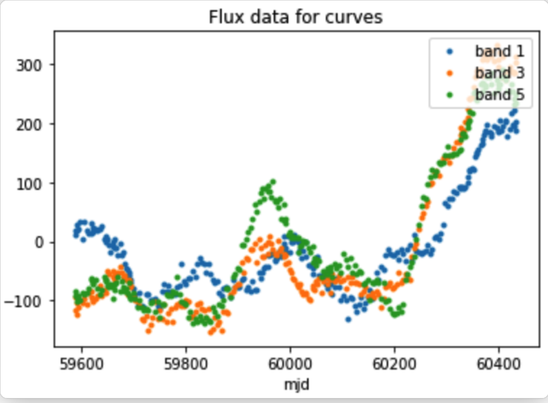












Now for each sampled light curve, we want to extract features for further classification.

Here I consider two types of features:

1. Features directly from meta data

- `ra` and `decl`: According to the analysis above, distribution of classes are not uniform in (ra,dec) coordinate system. So using this “location” information may help us do classification.
- `host_photoz` and `host_photoz_err`: As mentioned before, `host_photoz` is an estimator of the distance between us and the target source. This “depth” information is useful

2. Features from our sampled curve

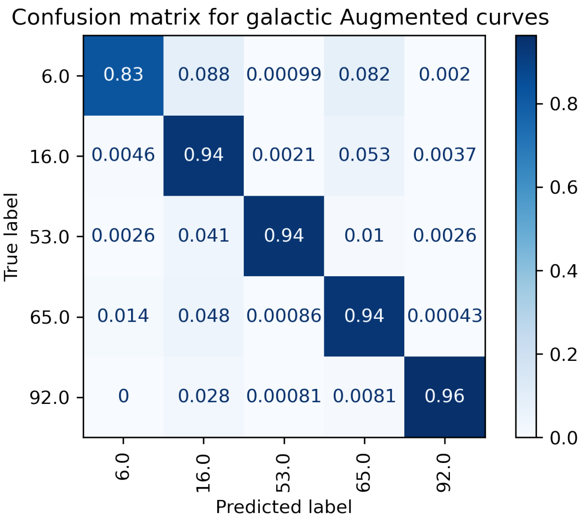
- `max_ratio_blue,min_ratio_red,max_ratio_blue,min_ratio_red`: Maximum/minimum of relative differences between flux in band 1,3(blue) and 3,5(red). These features describe the variability among passbands.
- `max_flux`: Maximum flux for passband 3.
- `time_bwd_max_0.2,time_max_0.5`: Time difference for passband 3 between the time for maximum flux and nearest time for less than 80%/50% flux. This a measure of period length.
- `ratio_flux`: Ratio of the maximum to the range of flux in passband 3.
- `max_dt`: Time difference between the time for maximum flux in band 1 and band 5.
- `skewness`: Skewness for flux in band 3.
- `Kurtosis`: Kurtosis for flux in band 3.
- `length_param`: we fitted scale parameter $\rho_t$.
- `skewness_g_i,Kurtosis_g_i,skewness_i_y,Kurtosis_i_y`: skewness/Kurtosis of relative relative differences between flux in band 1,3 and 3,5.

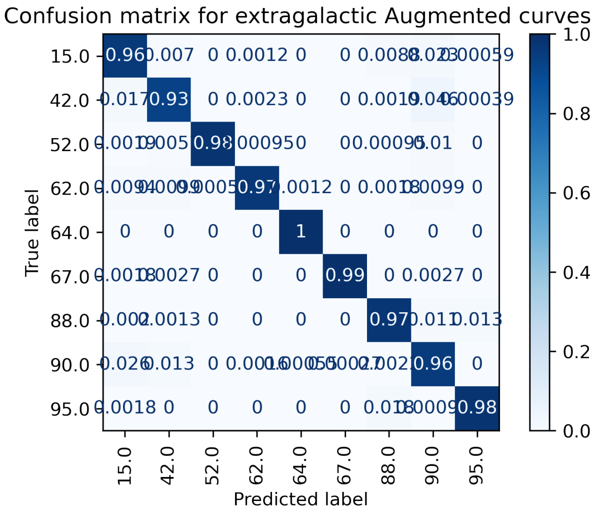
In total, we have 20 features for each generated curve.

## 4.Classification and analysis

I use **random forest** from python package `sklearn.ensemble` as my classifier for simplicity. There are **two random forests** separately for galactic sources and for extragalactic sources. For both random forests, the number of trees is set to be 100. For each tree, a small depth: 30, is chosen to avoid overfilling. We find tuning these hyperparameters brings little improvement.

First I randomly select $\frac{1}{5}$ data as training and the remaining as testing data, our random forests give 95.2% prediction accuracy on testing data. This is a pretty high accuracy for our classification task with 14 classes. The confusion matrices for galactic sources(left) and extragalactic sources(right) are shown below:

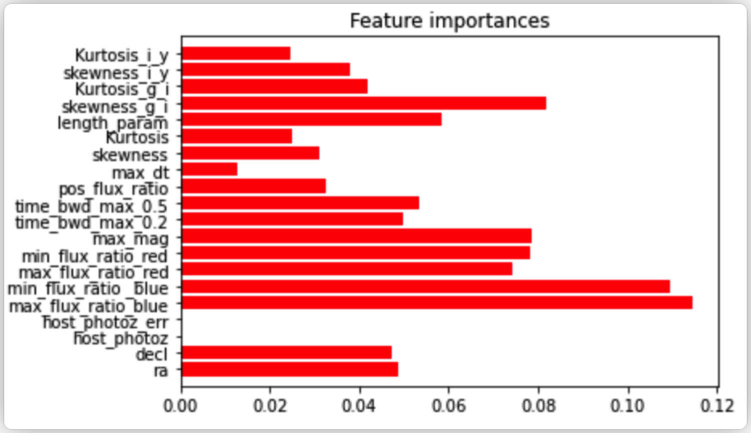


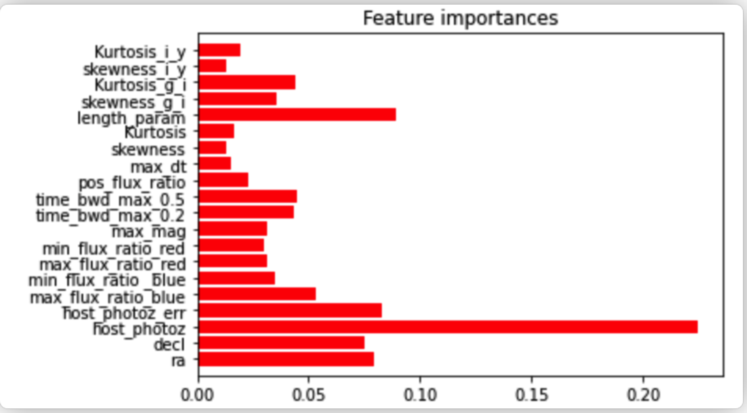


Remember in my final presentation, classification results for class 52 and 67 are terrible and can be explained by imbalanced classes in training data. Now as each class has approximately the same number of augmented data, this problem is solved as expected.

It is also possible to inspect the predicted probabilities for each class by calling `.predict_proba()` method in python.

Moreover, the impurity-based feature importance can be calculated to illustrate the influences of features(up is for galactic classifier and down is for extragalactic classifier):



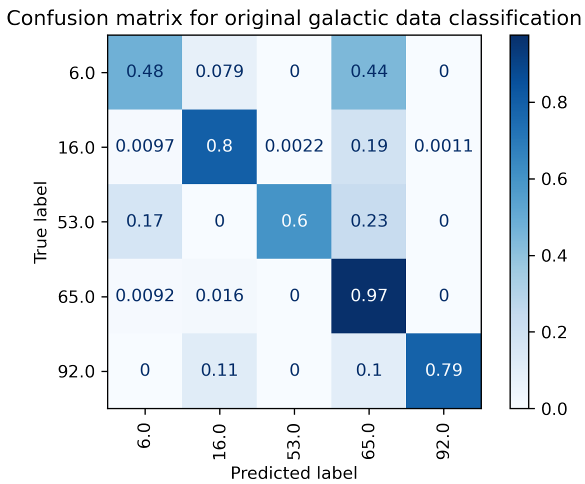


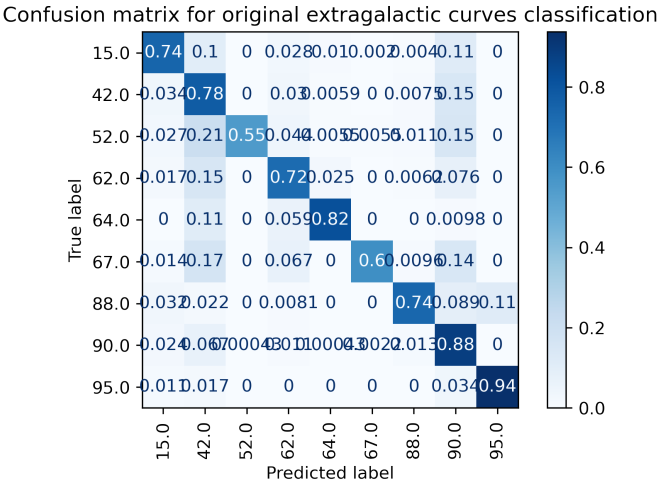
- As expected, for extragalactic classes, the `host_photoz` plays the most important role in our classification. This can be explained as the distributions of different classes of astronomical sources are highly dependent on the their distance from us. Some astronomical sources may usually be close to us and some may only exist in the “deep part” of our universe. This re-emphasizes the importance of getting accurate `host_specz` estimator, which happens to be an wildly-studied task in astronomy.
- Features except `host_photoz` and `host_photoz_err` play similar roles in galactic and extragalactic classifications.

At the end, we use these 20% augmented training data to do classification on the mean prediction(posterior means) of original curves. Now we get 81.6% accuracy, which is better than what we got in final presentation(73%). This improvement is due to:

- Hyperparameters in Gaussian process fitting are more carefully tuned.
- Training data are “balanced” by data augmentation process.
- More features are used.

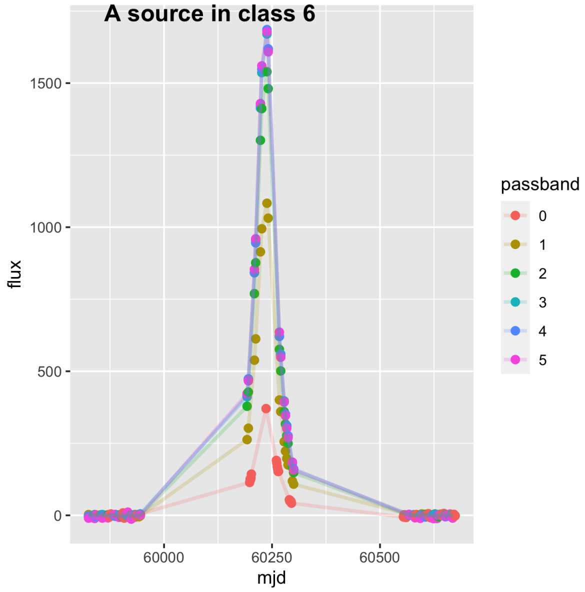
Again we show the confusion matrices below(left: galactic sources, right: extragalactic sources):

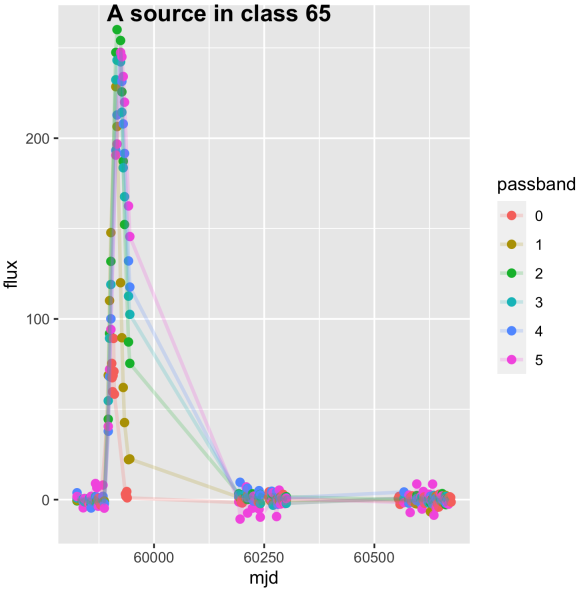




For class 6,52,53,67, the accuracies are relative low, between 0.48 and 0.6. This can be explained by following facts:

- In total, there is only 30 samples in class 53.
- For the rest, take class 6 as example. We notice about half curves in class 6 are classified to class 65. This is because these two classes have pretty similar pattern, thus our features cannot successfully distinguish them. This means more features are needed for better performance. Two light curves from class 6 and 65 are shown below:


A source in class 6
flux
mjd
passband


A source in class 65
flux
mjd
passband