# From FATS to feets: Further improvements to an astronomical feature extraction tool based on machine learning

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### Abstract

Machine learning algorithms are highly useful for the classification of time series data in astronomy in this era of peta-scale public survey data releases. These methods can facilitate the discovery of new unknown events in most astrophysical areas, as well as improving the analysis of samples of known phenomena. Machine learning algorithms use features extracted from collected data as input predictive variables. A public tool called Feature Analysis for Time Series (FATS) has proved an excellent workhorse for feature extraction, particularly light curve classification for variable objects. In this study, we present a major improvement to FATS, which corrects inconvenient design choices, minor details, and documentation for the re-engineering process. This improvement comprises a new Python package called *feets*, which is important for future code-refactoring for astronomical software tools.

*Keywords:* Astroinformatics, Machine learning algorithm: Feature selection, Software and its engineering: Software post-development issue

#### 1. Introduction.

Machine learning (ML) has proved to be an important tool for data analysis in astronomy. Numerous projects such as AstroML (VanderPlas et al., 2014), - UPSILoN (Kim and Bailer-Jones, 2016), MeSsI (de los Rios et al., 2016), and Feature Analysis for Time Series (FATS)(Nun et al., 2015) have been developed to help astronomers use the ML approach. Languages such as R<sup>1</sup> and Python<sup>2</sup> provide massive collections of ready-to-use packages for complex data analysis and a large number of ML tools. However, if we conduct in-depth analysis of these systems, it is apparent that some projects lack adequate software engineering design (Cowling, 1998), and thus they are often difficult to test, maintain, and extend, and some of these solutions may also under-perform in terms of speed and memory. Moreover, many projects run in critical environments and process large volumes of data over short timescales, and thus they can be inefficient if they are not optimized correctly. Thus, in simple terms, many scientific systems have a "bad code smell" (Tufano et al., 2015).

According to Fowler, code smell is a:

... a surface indication that usually corresponds

to a deeper problem in the software; and we currently know that *most of times code artifacts are affected by so-called "bad smells" since their creation...* (Fowler, 2006).

In these cases, the most pragmatic solution is to replace most of the code for a superior implementation, but to avoid any functional changes. This type of process is called *code refactoring* (Fowler and Beck, 1999).

In this study, we employed a code refactoring process to provide a more robust time-series feature extraction library based on the *FATS* project (Nun et al., 2015). The current version of FATS  $(1.3.6)^3$  is written entirely in Python and based on the numerical libraries comprising Numpy (Walt et al., 2011), Scipy (Jones et al., 2014), and StatsModels (Seabold and Perktold, 2010). FATS can extract up to 64 features from time series data inputs, and it also includes pre-processing functions and tools for importing data from the MACHO survey (Cook et al., 1995). The project tutorial for feature extraction<sup>4</sup> is instructive, but it lacks internal documentation, which is crucial when adding features to this otherwise excellent tool. In particular, we identified several limitations when we attempted to use FATS for classifying periodic variable stars from large data sets, such as the

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<sup>&</sup>lt;sup>1</sup>https://www.r-project.org/

<sup>&</sup>lt;sup>2</sup>https://www.python.org/

<sup>&</sup>lt;sup>3</sup>https://pypi.org/project/FATS

<sup>&</sup>lt;sup>4</sup>http://isadoranun.github.io/tsfeat/ FeaturesDocumentation.html

eaturesDocumentation.ntm1

VVV/VVV(x) (Catelan et al., 2011; Minniti, 2018) projects. Thus, we engineered an upgrade, which was carefully designed to build on the strengths of FATS by re-utilizing as much code and documentation as possible.

The remainder of this study is organized as follows. In section 2, we explain the feature extraction formalism and the relevance of automatic classification. In section 3, we consider the original project to identify advantages and weaknesses. The theoretical background of the re-engineering process and the selected actions required to implement *feets* are described in section 4. In section 5, we provide detailed explanations of the internal details that make *feets* a better choice for extracting time series features. Finally, in section 6, we give our conclusions and suggestions for future improvements to the FATS project.

#### 2. Feature engineering and ML

ML algorithms can be applied to large volumes of data in order to improve their performance at a given task (Samuel, 1959). These tasks may include classification, regression, optimization, or clustering, which are the most common ML applications (Michalski et al., 2013). The data employed may originate from a wide range of sources, but individual observations are always represented by a set of values called features. The process conducted for defining and extracting these features is called feature engineering. The highly specific nature of the feature engineering process makes it expensive, difficult, and time consuming, where it requires expertise in the area of application, and it is also the most critical step in a ML project (Ng, 2013).

#### 3. FATS

The FATS tool is used to extract characteristics from time series data. In particular, the FATS project aims to standardize the feature extraction process for astronomical light curves. FATS is built on top of the Python scientific stack (Numpy and Scipy) and it also uses StatsModels for additional statistical analysis.

#### 3.1. Simple example

A sample from the original documentation is shown below to clearly illustrate the different components of FATS.

The library receives as input the time series data and returns as output an array with the calculated features. Depending on the available input the user can calculate different features. For example, if the user has only the vectors magnitude and time, just the features that need this data will be able to be computed.

Obviously the number of data points, data cadence, etc. will also influence the number of possible features.

In order to calculate all the possible features the following vectors (also termed as raw data) are needed per light curve:

• magnitude

- time
- error
- magnitude2
- aligned\_magnitude
- aligned\_magnitude2
- aligned\_time
- aligned\_error
- aligned\_error2

>>> import numpy as np

where 2 refers to a different observation band. It should be noted that the magnitude vector is the only input that is strictly required by the library because it is necessary for calculating all the features. The remaining vectors are optional because they are only needed by some features. Thus, if the user does not have these additional data or time series other than light curves are being analyzed, it is still possible to calculate some of the features (...)

We illustrate this point with the following Python code, which calculates features for a randomly generated light curve. Only magnitude and time data are used, so the smallest feature set will be obtained. This code is also based on the FATS tutorial.

```
>>> import FATS
# randomly generate the data
>>> magnitude_ex = np.random.rand(30)
>>> time_ex = np.arange(0, 30)
# create the light curve array with the same
# order as the previous list
>>> lc_example = np.array([magnitude_ex, time_ex])
# create the feature space (this object serves
# as an entry point for extracting all the features)
# by specifying the available data
>>> fs = FATS.FeatureSpace(
        Data=['magnitude','time'])
. . .
Warning: the feature Beyond1Std could not be
   calculated because
  ['magnitude', 'error'] are needed.
  . . .
Warning: the feature CAR_mean could not be
   calculated because
  ['magnitude', 'time', 'error'] are needed.
# calculate the features of the light curve
>>> fs.calculateFeature(
      lc_example).result("dict")
{'Amplitude': 0.46422830004583993,
 'AndersonDarling': 0.69055170152838952,
 'Autocor_length': 1.0,
 'Con': 0.0,
```

```
'Eta_e': 1.2660816816234817,
...
'Period_fit': 0.99987790236635843,
'Psi_CS': 0.25119898781877714,
'Psi_eta': 1.4069202501024807,
'Q31': 0.47029269745864666,
'Rcs': 0.21319202165853643,
'Skew': 0.19709543035122007,
'SmallKurtosis': -0.93310208660425609,
'Std': 0.28904604267318268}
```

#### 3.2. Functionalities

In addition to the previous example, FATS provides the following functionalities.

Features Extraction Framework: FATS includes a simple tool for creating your own feature extractor. Every feature extractor is a python class inside the FATS.FeatureFunciontLib module. This class must contain object *attributes* that define the data required for the light curve and a fit() *method* used for calculating the feature. The following code is an example of a class that returns the number of observations in a time series.

```
class Count(Base):
  def __init__(self):
    # this attribute sets the
    # data required to calculate the feature
    self.Data = ['time']
  def fit(self, data):
    # the extractor retrieves the
    # time data from the light curve
    time = data[1]
    # finally, the extractor simply
    # returns the number of
```

```
# observations
```

return len(time)

Next, the extractor can be used as follows:

**Time Series Preprocessing:** Two functions are integrated for light curve data pre-processing, where the first is a time series error parameter based on a sigma-clipping algorithm (as implemented in the FATS.Preprocess\_LC class) and the second is a class called FATS.Align\_LC for aligning two time series. The documentation suggests that these functionalities are used before any features are extracted.

#### MACHO-survey Light-Curve Parser: The

FATS.ReadLC\_MACHO class retrieves the magnitude, time, and error from a given MACHO-id object (the id is assigned in the MACHO survey). This implementation does not search any of the data from the MACHO survey, but instead the user is responsible for downloading the light curve to the current working directory.

#### 3.3. Advantages and disadvantages of FATS

From a software engineering perspective, many design decisions in the FATS project are good implementations, whereas others are inadequate. In the following, the "good" design decisions are described in short paragraphs, before focusing on the problematic design decisions.

#### 3.3.1. Good design choices

A good design choice in FATS is separating the API<sup>5</sup> into two parts as follows.

- 1. Extraction is configured in the FATSEeatureSpace class.
- 2. The extraction of configured features is implemented as a class hierarchy inside the FATSFeatureFunciontLib module.

This split between the functionality for analysis (FATSEeatureSpace) and the creation of the feature extraction framework simplifies the operation of the system, but allows the possibility of implementing complex feature extractors. In addition, as noted above, preprocessing and MACHO light curve manipulation are not associated directly with the core functionality of the library, but instead they are provided as an additional option in the project.

#### 3.3.2. Criticisms

We consider several weak aspects of the current FATS implementation where the code is analyzed in depth. Some problems are simple style errors. Others are related to the development process and design bugs, which may cause errors and limitations during feature extraction.

The complete experiment that forms the basis of many of our criticisms can be found at: https: //github.com/carpyncho/feets\_paper/blob/master/ reports/FATS\_tests.ipynb

**Style and Maintainability** Python has a strict coding style defined in Python Enhancement Proposal 8 (PEP-8)<sup>6</sup>. This document defines guidelines for making code easy to understand by any Python developer. When a project follows these guidelines, as well as others such as PEP-20<sup>7</sup> (related to the philosophy behind python design), the Python community refers to the code as "Pythonic" (easy to understand and maintain). PEP-8 errors can be checked easily

<sup>&</sup>lt;sup>5</sup>Abstract programming interface: The collection of functions, classes, and objects that the programmer can use the library.

<sup>&</sup>lt;sup>6</sup>https://www.python.org/dev/peps/pep-0008/

<sup>&</sup>lt;sup>7</sup>https://www.python.org/dev/peps/pep-0020/

with several tools such as flake8<sup>8</sup> and pylint <sup>9</sup>, so avoiding style errors is a straightforward task.

FATS does not adhere to the recommendations and 828 style errors were found in 1249 lines of code in a recent executed count (i.e., 66% of the lines contained errors if we assume a uniform distribution of errors).

**Global Configurations** The FATS documentation states the following<sup>10</sup>.

**Note:** Some features depend on other features and consequently must be computed together. For instance, Period\_fit returns the false alarm probability of the estimated period. Thus, it is also necessary to calculate the period PeriodLS.

These dependencies are implemented as global variables. For example, we can check this with the StructureFunction\_index\_21 class from the FATS.FeatureFunctionLib module.

```
class StructureFunction_index_21(Base):
1
2
     def __init__(self):
3
       self.Data = ['magnitude', 'time']
4
     def fit(self, data):
6
         magnitude = data[0]
          time = data[1]
          global m_21
10
          global m_31
11
          global m_32
12
13
          # more code here
14
15
         m_21, b_21 = np.polyfit(sf1_log, sf2_log, 1)
16
         m_31, b_31 = np.polyfit(sf1_log, sf3_log, 1)
17
         m_32, b_32 = np.polyfit(sf2_log, sf3_log, 1)
18
19
         return m_21
20
```

According to this example, the m\_21, m\_31, and m\_32 (lines 16–18) variables are calculated and stored in the global environment/module level (lines 10–12) but only the m\_21 value is returned (line 20).

In addition, if we check the StructureFunction\_index\_31 class in the same module:

class StructureFunction\_index\_31(Base):

2

FeaturesDocumentation.html

```
def __init__(self):
3
       self.Data = ['magnitude', 'time']
4
5
     def fit(self, data):
6
        try:
           return m_31
         except:
9
           print ("error: please run "
10
                   "StructureFunction_index_21 "
11
                   "first...")
12
```

we can see that this class is only used to retrieve the m\_31 variable from the global environment (line 31), or to print an error to the console (line 10).

This design choice creates a bug, which can be exploited to retrieve incorrect values according to the following simple procedure.

1. First, import the modules and create two synthetic light curves: normal\_lc (the magnitudes are generated from a Gaussian distribution of values) and uniform\_lc (the magnitudes are generated from a uniform value distribution).

```
>>> import numpy as np
>>> import FATS
>>> mag = np.random.normal(size=10000)
>>> time = np.arange(10000)
>>> normal_lc = [mag, time]
```

```
>>> mag2 = np.random.uniform(size=10000)
>>> time2 = np.arange(10000)
>>> uniform_lc = [mag2, time2]
```

2. Second, create a feature space from which to extract the main built-in features comprising StructureFunction\_index\_21 and StructureFunction\_index\_31 from the normal light curve (normal\_lc).

```
>>> fs_normal = FATS.FeatureSpace(
... featureList=[
      'StructureFunction_index_21',
. . .
      'StructureFunction_index_31'])
. . .
# extract the features
>>> fs.calculateFeature(normal_lc)
>>> result = fs.result(method='dict')
# print the results
>>> print "Normal LC:"
>>> for f, v in result.items():
      f = f.split("_", 1)[-1]
      print " {} = {}".format(f, v)
. . .
Normal LC:
  index_21 = 1.97547953389
```

```
index_31 = 3.05091739197
```

3. Create a **new** feature space and try to extract only the StructureFunction\_index\_31 feature from

<sup>&</sup>lt;sup>8</sup>http://flake8.pycqa.org

<sup>&</sup>lt;sup>9</sup>https://www.pylint.org/

<sup>&</sup>lt;sup>10</sup>http://isadoranun.github.io/tsfeat/

the uniform light curve. (uniform\_lc). The value obtained should be the same as that for the StructureFunction\_index\_31 of the normal light curve.

```
>>> fs2 = FATS.FeatureSpace(
    ... featureList=[
    ... 'StructureFunction_index_31'])
# extract the features
>>> fs2.calculateFeature(uniform_lc)
>>> result = fs2.result(method='dict')
>>> print "Bad Uniform LC:"
>>> for f, v in result.items():
    ... f = f.split("_", 1)[-1]
    ... print " {} = {}".format(f, v)
Bads Uniform LC:
    index_31 = 3.05091739197
```

The only way to avoid this problem is to calculate StructureFunction\_index\_21 by default for all of the input light curves.

```
>>> fs3 = FATS.FeatureSpace(
... featureList=[
      'StructureFunction_index_21',
. . .
      'StructureFunction_index_31'])
. . .
# extract the features
>>> fs3.calculateFeature(uniform_lc)
>>> result = fs3.result(method='dict')
>>> print "Uniform LC:"
>>> for f, v in result.items():
      f = f.split("_", 1)[-1]
. . .
      print " {} = {}".format(f, v)
Uniform LC:
  index_{21} = 1.89689583705
  index_{31} = 2.74650784403
```

In fact, the same bug affects all of the features stored using a global configuration: Period\_fit, Psi\_CS, CAR\_tau, CAR\_mean, the *Fourier* components, and StructureFunction\_index\_31 and StructureFunction\_index\_32, as mentioned above.

**Python exit** The Python language defines errors as exceptions<sup>11</sup> so in the presence of any misconfiguration, some exceptional states are created to inform the caller code that "something has gone wrong."

For example, if we want to write a division function that fails with a divisor equal to 0, we could write the following.

>>> def division(a, b):
... if b == 0:
... raise Exception("b can't be 0")
... return a / b

The following result is obtained if the function is called.

```
>>> result = division(1, 2.)
>>> print result
0.5
>>> result = division(1, 0)
Traceback (most recent call last):
    ...
    raise Exception("b can't be 0")
Exception: b can't be 0
```

If it is desirable to print the null Python value None when an exception occurs so it is possible to manage the error with the try-except construct.

```
>>> try:
... result = division(1, 0)
... except Exception:
... result = None
>>> print result
None
```

This simple example shows how Python can be used by the programmer to correctly manage exceptional states: *if you do not know how to deal with a configuration, then throw an exception and ignore it without halting the system.* 

The error exceptions provided to the programmer by Python can be reduced to two basic types: BaseExceptions and Exceptions. The first type comprises exceptions that may only be managed in very unusual cases, such as SystemExit.

The SystemExit exception errors are raised when the function sys.exit() is called. This function call turns off the virtual machine and sends the exit code to the operating system. For example, the following piece of code:

```
>>> import sys
>>> sys.exit()
```

ends the Python virtual machine and sends a 0 value (no error) to the operating system.

In FATS, this occurs when a FeatureSpace is configured incorrectly and the Python virtual machine is turned off. The system becomes unstable at least inside a multiprocessing environment (such as a web server, pipeline, or simple multi-core calculation). The following two codes reproduce this error.

#### 1- Ask for an invalid feature

\$ python
Python 2.7.6 (default, ...)
>>> import FATS
# ask for a nonexistent feature

<sup>&</sup>lt;sup>11</sup>Anomalous or exceptional conditions requiring special processing

#### 2- Send an invalid configuration for a feature

```
$ python
Python 2.7.6 (default, ...)
>>> import FATS
# ask for a nonexistent feature
>>> FATS.FeatureSpace(
... featureList=['Std'], Std=(1,2,3))
error in feature Std
# python ends here
```

The following code may manage this error.

```
>>> import FATS
# ask for a nonexistent feature
>>> try:
>>> FATS.FeatureSpace(
... featureList=['Std'], Std=(1,2,3))
... except:
... # some manipulation
```

However, as mentioned above, the SystemExit was not designed to be managed.

**Python 3** Python 3 is a new language part of the Python family to replace the 2.7.x branch at 2020<sup>12</sup>. This version is **backward incompatible** with Python 2.x but it includes several improvements in terms of expressibility and velocity<sup>13</sup>

Currently, all the foundations of the Python scientificstack, based on which FATS is built, have already been ported to the 3.x branch, but the code base of the project is still Python 2.x only<sup>14</sup>. This issue essentially represents an impending death sentence for the package in the next two years.

- Light Curve Order This is a minor issue. Most of the light curve data sets represent the data in the following format: *time/magnitude/magnitude-error*, whereas FATS uses the following format: *magnitude/time/magnitude-error*. Thus, preprocessing is required in many cases.
- **Inefficient Routines** In FATS, some performance issues are linked with the calculation of two features: MaxSlope and PeriodLS. The code in the MaxSlope class is displayed below for analysis.

```
class MaxSlope(Base):
```

```
2
```

.....

```
<sup>13</sup>https://speed.python.org/comparison/
```

```
<sup>14</sup>This issue are already been reported to the authors at: https://github.com/isadoranun/FATS/issues/7
```

```
magnitudes, the maximal first difference
4
     (value of delta magnitude over delta time)
5
6
     def __init__(self):
7
       self.Data = ['magnitude', 'time']
9
     def fit(self, data):
10
       magnitude = data[0]
11
       time = data[1]
12
       slope = (
13
         np.abs(magnitude[1:] - magnitude[:-1]) /
14
          (time[1:] - time[:-1]))
15
       np.max(slope)
16
17
       return np.max(slope)
```

The np.max function is called two times in lines 16 and 17. The result from line 16 is not used, so this calculation can be removed.

The problem is more complicated for PeriodLS because the full implementation of the Lomb–Scargle Method (VanderPlas, 2018), which is included with FATS, is programmed in IDL Language (Landsman, 1995)<sup>15</sup> based on the published Numerical Recipes (Press, 2007) routine. This makes the code difficult to maintain and it has some performance issues due to the incorrect usage of the *Numpy* library. Furthermore, this implementation of the Lomb–Scargle methodology is applied iteratively to calculate the nine Fourier features.

We extracted a high number of features for a particular light curve in the MACHO Survey and the computational time decreased by 20% when all the features calculated using the Lomb–Scargle Periodogram were neglected.

**Testing and Coverage** Measuring the qualitative and quantitative metrics for a software project involves **unit testing** and *code coverage*.

*Unit testing* attempts to show that each part of the program is correct (Jazayeri, 2007) by isolating independent pieces of code and running tests on them. Code coverage measures the percentage of code executed by the unit tests (Miller and Maloney, 1963).

In the FATS tutorial, a static result is presented based on a test of invariance using unequal sampled data <sup>16</sup> The project has 19 automated unit testing cases and only one currently fails<sup>17</sup>. Unfortunately, the entire test suite only executes 62% of the entire code, which is significantly below the requirement of 90% adhered to by other astronomy projects such as Astropy (Robitaille et al., 2013).

<sup>3</sup> Examining successive (time-sorted)

<sup>&</sup>lt;sup>12</sup>https://www.python.org/dev/peps/pep-0373/

<sup>&</sup>lt;sup>15</sup>https://github.com/isadoranun/FATS/blob/master/FATS/ lomb.py

<sup>&</sup>lt;sup>16</sup>http://isadoranun.github.io/tsfeat/

FeaturesDocumentation.html#Appendix

<sup>&</sup>lt;sup>17</sup>This issue has been reported to the authors at:https://github.com/ isadoranun/FATS/issues/9

	AndersonDarling	StetsonJ	StetsonK
count	100000	1000000	100000
mean	0.6052	5.953862e+05	0.2047
std	0.2576	3.775754e+05	0.0662
min	0.0930	2.442287e+05	0.0342
25%	0.3796	4.204386e+05	0.1564
50%	0.5993	5.104198e+05	0.2036
75%	0.8427	6.616722e+05	0.2510
max	1.0000	4.056122e+07	0.4484

Table 1: Statistical analysis of the *AndersonDarling*, *StetsonJ*, and *StetsonK* features executed with 100,000 randomly generated Gaussian light curves.

**Some features do not produce the expected values** The FATS documentation <sup>18</sup> states the following.

- The feature *StetsonK* for a Gaussian magnitude distribution should take a value close to  $2/\pi = 0.798$ .
- For a Gaussian magnitude distribution, *StetsonJ* should take a value close to zero.
- For a normal distribution the *Anderson-Darling* statistic should take values close to 0.25.

To validate the documentation, we calculated these three features for 100,000 randomly generated Gaussian light curves and the results were not as expected. The results are presented in Table 1, which shows that the mean values for *StetsonK,AndersonDarling*, and *StetsonJ* differ by several orders of magnitude from the expected values.

**Missing Dependencies** The current version of FATS (1.3.6) is distributed in the same manner as any standard Python third-party package via a service called "Python Package Index" (PyPI)<sup>19</sup>, which allows the package to be installed in Linux distributions with the following simple bash command.

\$ pip install FATS

However, attempting to run this command would lead to a "missing packages" message and failure of the installation process. As mentioned above, FATS is built on top of the Python scientific-stack comprising libraries such as Numpy, Scipy, and Pandas, as well as specific libraries including Matplotlib and StatsModels, which are required but not installed automatically. The user is responsible for manually installing these packages in order to start working with the project. In addition, the standard Python scientific plotting library called Matplotlib is not used for any of the core tasks in FATS, which is an unnecessary obstacle. Most of these problems are fixed in the current code base in the GitHub repository, but no new releases have been made public since the aforementioned version 1.3.6 on June 7, 2015.

**Missing in-code documentation** The only documentation for the project is the tutorial. Internally, all of the components are undocumented.

Two particular cases that are not mentioned in the tutorial are as follows.

• Structure	functions:		the
StructureFu	nction_index_21,		
StructureFu	nction_index_22,		and
StructureFu	nction_index_31	features	are
part of the FA	TS codebase in GitH	lub (since F	ebru-
ary 9, 2016),	but other than the co	mment post	ed in
the version co	ontrol commit statin	g that: "Ad	dding
Structure Fun	ction from Simonetti	et al. 198	4"( <sup>20</sup>
there are no d	escriptions of these f	features and	their
interpretations			

• **Importing light curves toolbox**: The FATS documentation states the following.

In addition to the features library, we provide a basic toolbox for importing and preprocessing the data (...)

(...) the function ReadLC\_MACHO() receives a MACHO id (object id assigned in the MACHO survey) as an input and returns the following output: magnitude measurement, time of measurement, associated observational error (...)

A demonstration of how to import a MACHO light-curve is presented below (...)

However, the documentation is incorrect because ReadLC\_MACHO() receives a full path to a previously downloaded MACHO light curve.

#### 4. Code Refactoring: Improving FATS

In Section 1, we explained that bad design choices can be addressed using the code refactoring technique, thereby modifying the design of FATS but without changing its functionality. This is ensured by the following method.

- 1. First, all of the feature extractors in FATS are executed for an example light curve and the results are stored.
- 2. Second, a unit test case is conducted, which executes the same extractors and checks whether the results are the same as those stored in the stored file.

<sup>&</sup>lt;sup>18</sup>http://isadoranun.github.io/tsfeat/

FeaturesDocumentation.html

<sup>&</sup>lt;sup>19</sup>https://pypi.org/project/FATS/

<sup>&</sup>lt;sup>20</sup>Structure Functions commit: https://github.com/isadoranun/ FATS/commit/b45b5c1

- 3. Next, porting of the new architecture is commenced progressively while checking whether the test is still passed.
- 4. If an extractor directly changes the result for any feature extractor, then the test is modified in order to assess this change.

This approach where a test is specified and the code is then built is called test-driven development. This technique makes it easier to trust that each new piece of code written during the refactoring process is not generating new regression  $bugs^{21}$ .

After the initial test, the code refactoring process is divided into the following six sequential tasks.

- 1. Update each feature extraction function while maintaining the same behavior<sup>22</sup>.
- 2. Write a new FeatureSpace stateless class.
- 3. Test to ensure that each feature extractor returns reasonable values, at least for usual expected inputs.
- 4. Continue by performing more tests until 90% code coverage is achieved.
- 5. Include documentation for the features and extractors inside the code as Python docstrings<sup>23</sup>.
- 6. Port the tutorial. This process includes auto-generating documentation for every feature extractor.

## 5. Results: feATURES eXTRACTOR for tIME sERIES (feets)

Due to the radical restructuring of the project, we decided to create a new package called *feATURE eXTRACTOR FOR tIME sERIES* (*feets*). The FATS functionalities can be found inside this new *feets* library and most of the issues described in Section 3.3.2 have been addressed. Error handling strategies were applied in cases where this was not possible in order to inform the user about any possible issues with the results.

#### 5.1. Clear code, high coverage rate, and public API documentation

Testing in *feets* includes 49 unit test cases that are currently passed, with up to 90% code coverage. The source code is completely PEP8 style compliant. A continuous integration<sup>24</sup> tool automatically executes the tests whenever a new version of the project is uploaded to the public code repository. Finally, documentation was written for most of the public objects, classes, and functions in *feets*. This documentation is compiled automatically and published on the following page: http://feets.readthedocs.io.

#### 5.2. Support for Python 3.x

The current version of  $feets^{25}$  (0.4) is compatible with Python versions 2.7, 3.5, 3.6, and 3.7, where compatibility is achieved via the *six* library<sup>26</sup>.

<sup>25</sup>https://pypi.org/project/feets/#history

#### 5.3. Better encapsulation of extractors

The extractors were redesigned in order to avoid global variables and they now return a fixed set of features because the FeatureSpace is in charge of discarding the unused ones. The new infrastructure is capable of making compile-time checks for any extractor introduced by a user in order to avoid unexpected behavior during feature extraction.

Finally, a feets.register\_extractor function is provided, which os capable of including user-defined extractor classes in the *feets* functionalities. More detailed explanations of these topics can be found in the tutorial (http://feets. readthedocs.io/en/latest/#Library-structure).

#### 5.4. Exceptions and Warnings

If the user misconfigures the feets.FeatureSpace, an exception is raised instead of sys.exit(), which shuts down the entire Python virtual machine. In addition, a warning is shown when the user requests a feature from any of the extractors with inconsistent behavior: (*StetsonK*, *StetsonJ* (Richards et al., 2011), and *Anderson-Darling* (Kim et al., 2009)).

#### 5.5. Integration with Astropy and other dependencies

The homepage of the Astropy<sup>27</sup> project (Robitaille et al., 2013) states the following.

The Astropy Project is a community effort to develop a core package for astronomy using the Python programming language and improve usability, interoperability, and collaboration between astronomy Python packages.

Our decision to include the Astropy package was dependent on two objectives: to replace the built-in Lomb-Scargle <sup>28</sup> implementation of FATS with that distributed by the Astropy project in order to improve the performance of the period feature extractor; and to propose *feets* as part of the Astropy-Afiliated-Packages<sup>29</sup> in order to demonstrate a commitment to Astropy's goals for Python astronomy and astrophysics packages.

In addition to Astropy, each dependency in *feets* is included into the Python-Package-Index installer, so the project is ready to use with a single pip install feets command. Finally, Matplotlib was removed as a dependency.

#### 5.6. Other Enhancements

- The order of the input parameters was updated to *Time-Magnitude-Magnitude Error*, which is now consistent with most previous studies.
- The preprocessing functions were renamed in order to make them more intuitive. For example,

<sup>&</sup>lt;sup>21</sup>Regression is something that used to work, but no longer does

 $<sup>^{22} {\</sup>rm the}$  results must be the same for the same input in order to pass the initial test

<sup>&</sup>lt;sup>23</sup>https://docs.scipy.org/doc/numpy-1.14.0/reference/

<sup>&</sup>lt;sup>24</sup>https://travis-ci.org/carpyncho/feets

<sup>&</sup>lt;sup>26</sup>https://pypi.org/project/six/

<sup>&</sup>lt;sup>27</sup>http://www.astropy.org

<sup>&</sup>lt;sup>28</sup>https://github.com/isadoranun/FATS/blob/

<sup>6</sup>fcd852adf213a477fda878650be5b467a5dd0d8/FATS/lomb.py <sup>29</sup>http://www.astropy.org/affiliated/index.html

```
FATS.Preprocess_LC(
   mag, time, error).Preprocess()
FATS.Align_LC(
   time, time2, mag, mag2, error, error2)
```

was renamed as follows.

feets.preprocess.remove\_noise(
 time, mag, error)
feets.preprocess.align(
 time, time2, mag, mag2, error, error2)

• The feets.dataset module was included to retrieve light curves from the MACHO, OGLE-III(Udalski, 2004) survey as well as for creating synthetic light curves based on a set of random distributions of parameters (e.g., periods).

#### 6. Conclusions and Future Work

In this study, we redesigned a Python library for extracting times series features, where we addressed the design flaws of its predecessor. This new *feets* package is compatible with upcoming Python versions and it is fully documented. This package includes a larger test suite with 90% code coverage, greater extensibility, integration with more data sets, and has been being proposed to be including as Astropy affiliated package. The project was developed in a public repository, with more than 233 commits and five contributors. Future development will focus on the following three areas: incorporating new features, improving documentation, and possible integration with tools for interactively analyzing features.

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This research employed the http://adsabs.harvard.edu/, Cornell University xxx.arxiv.org repository, the Python programming language, the Numpy and Scipy libraries, and the other packages utilized can be found at the GitHub webpage for feets.

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