Detecting Exoplanets from NASA Kepler Data

Machine Learning Engineer Nanodegree
Capstone Proposal
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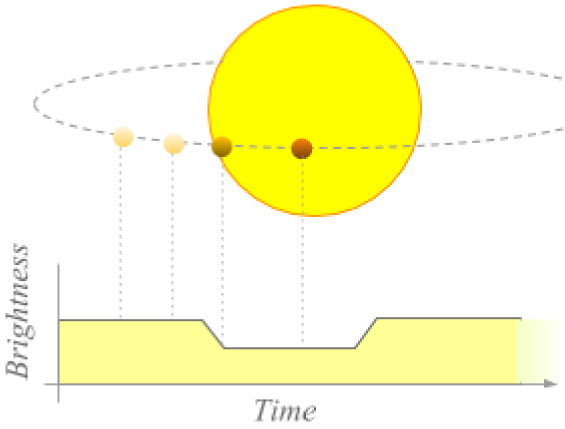
July 25, 2018

Domain Background

One of the Great Questions of our time is that of the existence of non-terrestrial life. Of special relevance is the search for life from outside our solar system, as that would suggest a separate origin of that life, showing evolution has produced life at least twice, and therefore possibly many times. As part of this quest astronomers have been looking for planets with similar conditions to earth in terms of size, solidity and temperature range. Such planets will then become candidates for further investigation.
The Kepler mission was launched in 2009 in order to monitor 156,000 stars in the areas of Cygnus & Lyra with the intention of detecting earth-like planets in the stars' habitable zones [Borucki, 2010]. The basic mechanism for detection is simple: monitor the light of a star over a period of time and look for periodic reduction in the brightness of the star for period in the range 2-16 hours [NASA, 2018], this dimming being caused by the obscuration of a small fraction of the stars light during the planets transit between the observer and the star.



Star light dimmed by transiting planet

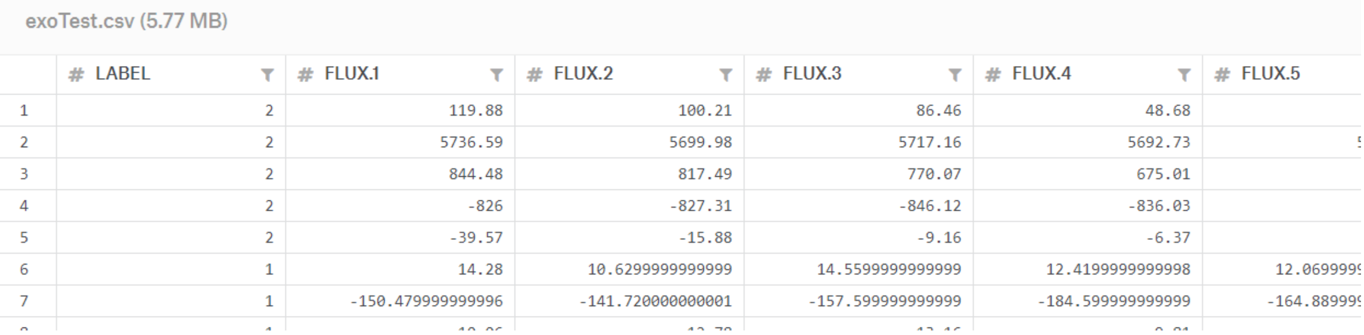
Problem Statement

The proposal is a two-class classification problem, to identify stars with planets given time-series data of stellar brightness from stars in the Kepler survey. The classification classes are "Planet Present" and "No Planet Present". The approach is to find periodic brightness variations in the range of 2-16 hours which would therefore suggest a transiting orbital body.
The input datasets being used are from NASA and were published for use in the Kaggle "Exoplanet Hunting" competition [Kaggle, 2018]. The output will be a single real number in the range [0.0 .. 1.0], representing the certainty of the presence of a planet.

Datasets and Inputs

The data has been cleaned by removing sensor artefacts, translating to a linear scale, removing likely cosmic ray artefacts, removing background flux and summing values over the photometric aperture of the target star image. They are then further pre-processed to allow for focusing and pointing artefacts, and for gaps in the time series [Jenkins, 2018].

The structure of the training dataset is simple. The files are presented as CSV files, one training set `exoTrain` and one test set `exoTest`. In the files there is 1 observation time-series per row. There are 5087 rows in the `exoTrain` file, and 570 rows in the `exotest` file. Each row consists of a single label, `LABEL`, then 3197 flux points in columns `FLUX.1` to `FLUX.3197` representing flux values from *t=1* to *t=3197*.



exoTest.csv (5.77 MB)

	# LABEL	# FLUX.1	# FLUX.2	# FLUX.3	# FLUX.4	# FLUX.5
1	2	119.88	100.21	86.46	48.68	
2	2	5736.59	5699.98	5717.16	5692.73	5
3	2	844.48	817.49	770.07	675.01	
4	2	-826	-827.31	-846.12	-836.03	
5	2	-39.57	-15.88	-9.16	-6.37	
6	1	14.28	10.6299999999999	14.5599999999999	12.4199999999998	12.0699999
7	1	-150.479999999996	-141.720000000001	-157.599999999999	-184.599999999999	-164.889999

The exoTest.csv data file

For this project we will generate training and validation datasets from the `exoTrain` dataset. Give the paucity of positive samples in the data, this will be manipulated so as to ensure a similar number of positives in each training set, by random sampling in the subsets of positive and negative samples. `exoTest` will be used as the test data. This can be achieved in code, or by use of an over-sampling library e.g. [Lemaitre, 2016].

The sampling interval for these Long Cadence files is a consistent 29.4 minutes or 56.7 mHz. The Nyquist frequency is 284 μHz [Murphy, 2018]. The variance of the flux measurements is wide and will need normalising.

Solution Statement

There is an experimental element to this project, and so two approaches will be taken which may be joined later.

Firstly the raw data will be pre-processed using Fourier transforms to identify cyclic features. A Fast Fourier Transform will provide additional features for the dataset based on any periodic elements in the data, and as the planets we are seeking have a clear range of orbital periods it may be of value [Garza, 2015]. Secondly a model will be constructed using 1D convolutional neural networks over the NASA time-series data, as per the approach in [Shallue, 2018].
The output of each of these models will then be fed into a multi-input model for comparison (parallel sub-networks for the time-series data and the generated Fourier analysis) [Chollet, 2018].

Benchmark Model

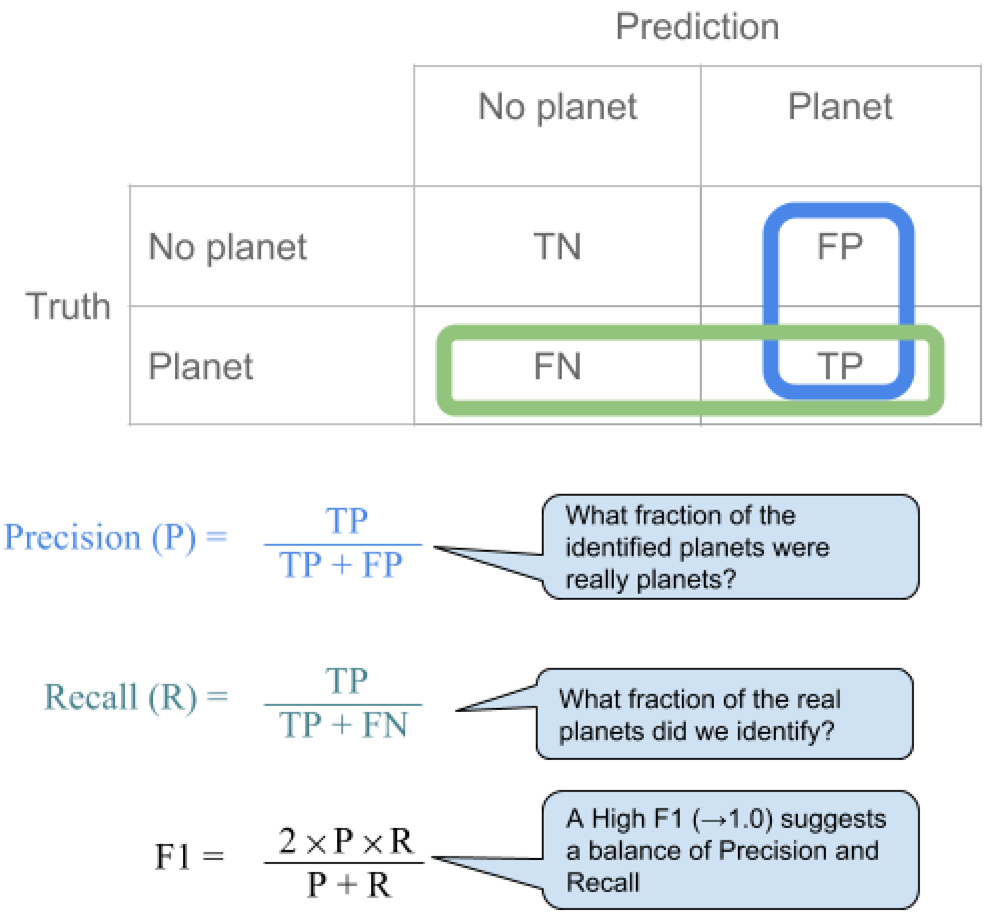
The model will be benchmarked against a random forest trained against the `exoTrain` training and evaluation sets as per the main model, then tested against `exoTest`. This will enable a direct comparison of performance between the benchmark model and the ANN model.

The data as supplied is fully labelled, so further comparison can be made with the analysis as performed by the Kepler Science Processing Pipeline. The Kepler model is, by design, more sophisticated than the one proposed herein:

> Ancillary engineering data and diagnostic information extracted from the science data are used to remove systematic errors in the flux time series that are correlated with these data prior to searching for signatures of transiting planets with a wavelet-based, adaptive matched filter. Stars with signatures exceeding 7.1σ are subjected to a suite of statistical tests including an examination of each star's centroid motion to reject false positives caused by background eclipsing binaries.
> [Jenkins, 2010]

Evaluation Metrics

Evaluation of the model is relatively simple given that this is a binary classification task with labelled data. Given the large skew in the dataset towards `no planet` we need to balance precision and recall. For publication purposes we might opt for high precision, so that the positives are more likely to be true-positives. However for research purposes higher recall will positively identify more of the actual systems with planets, at the expense of false positives. These false positives might still, though, be good candidates for further investigation given that they show hints of periodicity. For the purposes of this project we will use the F1 score.



		Prediction	
		No planet	Planet
Truth	No planet	TN	FP
	Planet	FN	TP

$$\text{Precision (P)} = \frac{TP}{TP + FP}$$

What fraction of the identified planets were really planets?

$$\text{Recall (R)} = \frac{TP}{TP + FN}$$

What fraction of the real planets did we identify?

$$F1 = \frac{2 \times P \times R}{P + R}$$

A High F1 (→1.0) suggests a balance of Precision and Recall

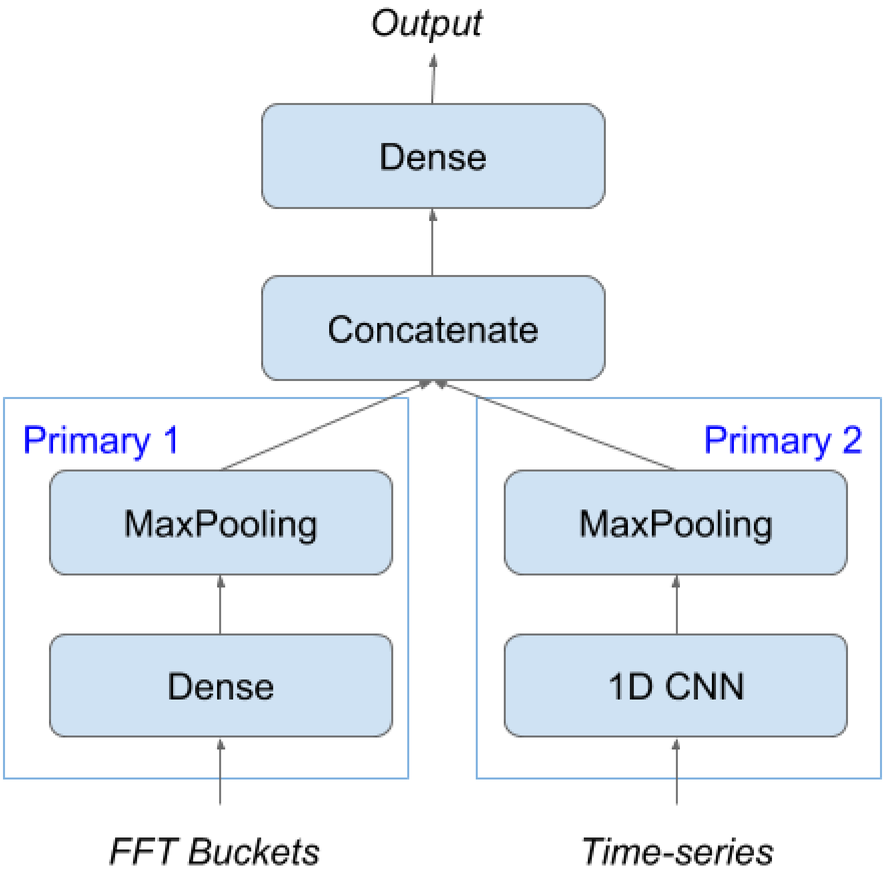
Project Design

The design of the project follows these steps:

1. Augment the data for training. The dataset has only about 1% positives, so construct a more balanced training set by randomly removing a proportion of the true negatives (this will be hyperparameter controlled and subject to tuning)

2. Pre-process using Fourier transforms to identify cyclic features. A Fourier frequency analysis provides additional features, and as the planets we are seeking have a clear range of orbital periods it may be of value [Garza, 2015].
3. **Primary Model 1** Train a sequential model on the Fourier frequency buckets. This presents a design challenge in deciding the model architecture, for which we will use 1d convolutions, given the aim is to identify spikes which are appropriate convolutional targets. Alternatively an LSTM RNN or a simple dense network could be used. Advice would be welcome.
4. **Primary Model 2** Train a second sequential model using 1D convolutions over the time-series data, as per the approach in [Shallue, 2018].
5. Construct a multi-input model for comparison (parallel sub-networks for the time-series data and the generated Fourier analysis) [Chollet, 2018].
6. Tune the hyperparameters to optimise the results.
7. Select final model - which might be either of primary models, or the composite model, depending on performance.

Note the primary models will each require an additional dense output layer if operating in isolation.



Keras Model Architecture

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