Supernova Classification Using Swift UVOT Photometry

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Abstract

With the great influx of supernova discoveries over the past few years, the observation time needed to acquire the spectroscopic data needed to classify supernova by type has become unobtainable. Instead, using the photometry of supernovae could greatly reduce the amount of time between discovery and classification. For this project we looked at the relationship between colors and supernova types through machine learning packages in Python. Using data from the Swift Ultraviolet/Optical Telescope (UVOT), each photometric point was assigned values corresponding to colors, absolute magnitudes, and the relative times from the peak brightness in several filters. These values were fed into three classifying methods, the nearest neighbors, decision tree, and random forest methods. We will discuss the success of these classification systems, the optimal filters for photometric classification, and ways to improve the classification.

Introduction

Type Ia supernovae (SNe Ia) are an important tool in observational cosmology and are characterized by a strong Si II absorption line and by an absence of a hydrogen absorption line in the spectroscopic data. In order to see these characteristics in the data, a telescope equipped with a spectrometer must be available. With the increased number of photometric observations of SNe, these spectroscopic follow-up observations become more difficult to keep up with. Instead, there has been an effort to classify SNe using their light curves.

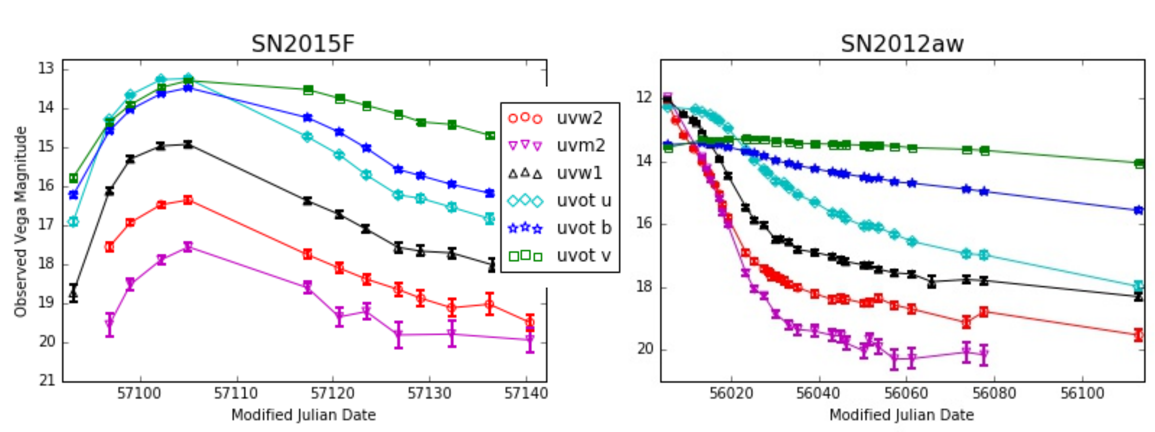

Figure 1. The comparison of light curves for type Ia (left) and IIP (right) SNe in the six Swift UVOT filters.

Machine learning algorithms have been implemented to classify SNe from light curves like those in Figure 1 (Kessler 2010, Lochner 2016). For this project we use the Python package *Scikit-learn* (Pedregosa 2011) to assess the success rate of three different classification methods in classifying SNe Ia. All three of the classifiers rely on characteristics defined by the user. From the Swift UVOT data, 22 characteristics (including 10 colors, 6 absolute magnitude values, and 6 relative times from the peak brightness in each of the filters) were assigned to each photometric point as well as one of the possible SN types (Ia, Ib, Ic, II). These data structures were separated randomly into training and testing sets and then fed into each classifier. The output classification of the testing sets were compared to the recorded classification to assess the success of the algorithm.

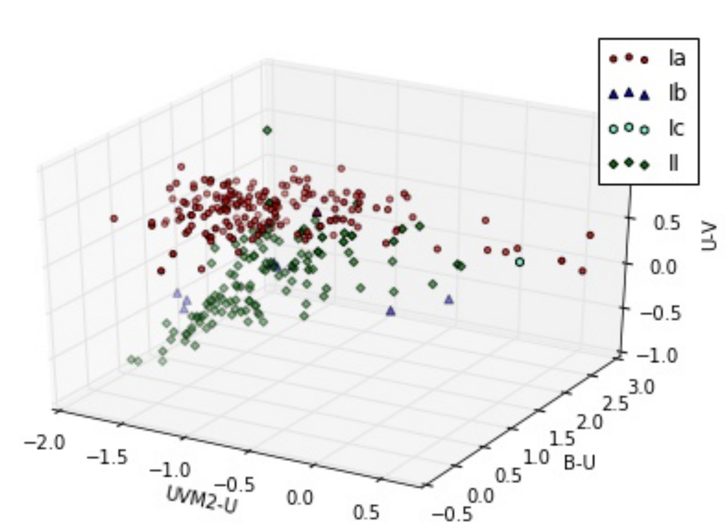

Figure 2. An example of separating SN types using only three colors.

Data

- The data, in six filters: uvw2, uvm2, uvw1, u, b, and v, comes from the Swift Optical/Ultraviolet Supernova Archive (SOUSA)
- Calculated absolute magnitudes using distance moduli from Cepheids, star brightness fluctuations, planetary nebula luminosity functions, and host galaxy velocities
- Of the 172 SN with sufficient observation data and calculated absolute magnitudes, 660 photometric points were available to use for the classifiers.
- The photometric points were randomly assigned to training (396 points) and testing (264 points) sets
- Each feature, or characteristic, was assigned a number:

#	Feature
0	uvw2-uvw1
1	b-v
2	uvm2-uvw1
3	u-v
4	uvw2-u
5	uvw2-uvm2
6	uvw1-u
7	uvw1-b
8	uvm2-u
9	b-u
10	reltime uvw2
11	reltime uvm2

#	Feature
12	reltime uvw1
13	reltime u
14	reltime b
15	reltime v
16	UVW2
17	UVW1
18	UVM2
19	U
20	B
21	V

Classifiers

- **K Nearest Neighbors Classification (KNN)** – Of the three classifiers, the KNN algorithm does not generate a model from which it draws conclusions. Instead it looks at the points in the training set and assigns a class to the new object based on its closest neighbors in the feature space. The space in which this classifier works is hard to visualize when there are more than three features. The *k* value indicates how many of the nearest neighbors the algorithm looks at. For this project, $k = 15$.
- **Decision Tree Classification (DT)** – This classifier builds a decision tree based on different cutoff values for all of the features fed into the program. These trees are more easily visualized when the feature list includes more than three characteristics.
- **Random Forest Classification (RF)**– Using the same main ideas as the DT classifier, this classifier creates many trees based on subsets of the dataset. The trees are then compared to each other to find the optimal decision tree.

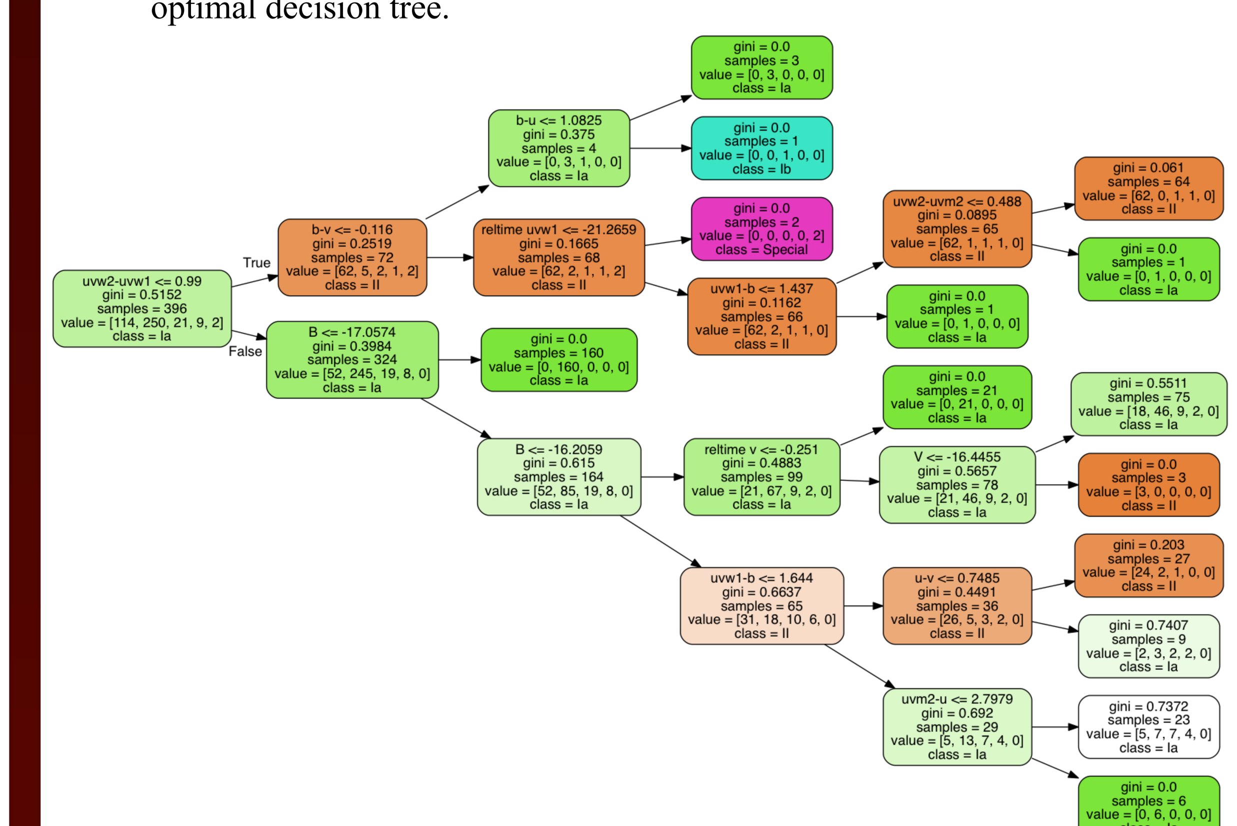

Figure 3. An example output for the decision tree classifier with each leaf showing the feature, Gini impurity, sample size, and dominant class.

Results

Classifier	Ia precision	Ia recall	Total score	Filters
KNN	0.71	0.98	0.73	all six
DT	0.82	0.98	0.81	
RF	0.76	0.99	0.79	
KNN	0.70	0.94	0.69	UV (uvw2,uvm2, uvw1)
DT	0.80	0.90	0.73	
RF	0.75	0.96	0.75	
KNN	0.75	0.94	0.72	visible (b,v,u)
DT	0.85	0.92	0.77	
RF	0.82	0.95	0.79	

- **Ia precision** - Of the photometric points classified as SNe Ia, how many were actually SNe Ia
- **Ia recall** – Of the points actually SNe Ia, how many were classified correctly
- **Total score** – Of all the points of all types, how many were classified correctly
- Because there are many different ways to define success for these classification systems, it depends on the reason for classification to determine which classifier would be the most appropriate for scientific use.
- The most successful classification algorithm from the Supernova Photometric Classification Challenge (Kessler 2010) produced a Ia precision of 0.79 and a Ia recall of 0.96.
- Removing either the visible or UV filters reduced the success in the classifiers in all of the metrics, except in the case of the removal of the UV filters, the Ia precision increased for all three classifiers

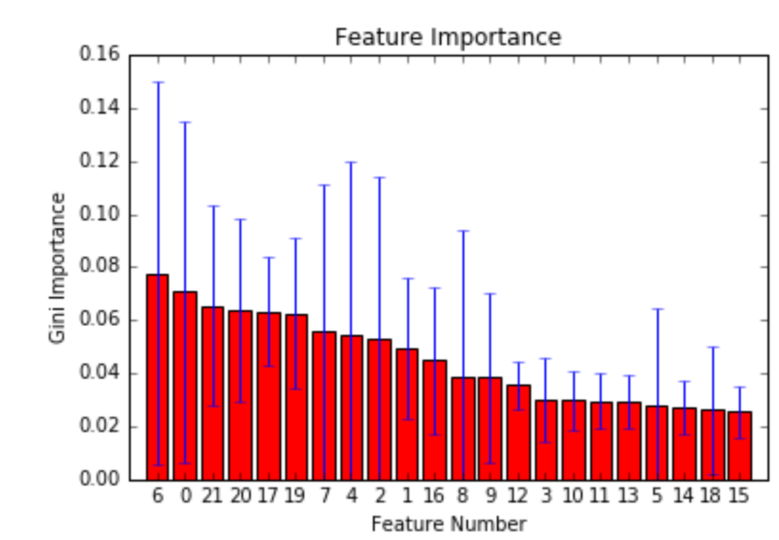

Figure 4. The normalized Gini importance of each feature found from the random forest classifier

- Figure 4 uses average the Gini importance or the Mean Decrease in Impurity (MDI) over 250 decision trees to show which features had the biggest impact on classification
- The large error bars indicate there is no feature that contributes significantly more than the others.

Future Work

Parameterizing the entire light curves instead of relying on individual photometric points could lead to a higher total score. To see if some of the misclassifications come from missing data, we could use simulated light curves with no epochs of missing observations. We could see if this process works on other transient objects.

References

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