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Classification of ASKAP VAST Radio Light Curves†

Umaa Rebbapragada[1], Kitty Lo[2], Kiri L. Wagstaff[1], Colorado Reed[3], Tara Murphy[2] & David R. Thompson[1]

[1]Jet Propulsion Laboratory, Pasadena, CA, 91109 USA
email: Umaa.D.Rebbapragada@jpl.nasa.gov

[2]Sydney Institute for Astronomy, University of Sydney, Sydney, NSW 2006, Australia

[3]Department of Physics, University of Iowa, Iowa City, IA 52242, USA

Abstract. The VAST survey is a wide-field survey that observes with unprecedented instrument sensitivity (0.5 mJy or lower) and repeat cadence (a goal of 5 seconds) that will enable novel scientific discoveries related to known and unknown classes of radio transients and variables. Given the unprecedented observing characteristics of VAST, it is important to estimate source classification performance, and determine best practices prior to the launch of ASKAP's BETA in 2012. The goal of this study is to identify light-curve characterization and classification algorithms that are best suited for archival VAST light-curve classification. We perform our experiments on light-curve simulations of eight source types and achieve best-case performance of approximately 90% accuracy. We note that classification performance is most influenced by light-curve characterization rather than classifier algorithm.

Keywords. ASKAP, VAST, radio astronomy, classification, data analysis

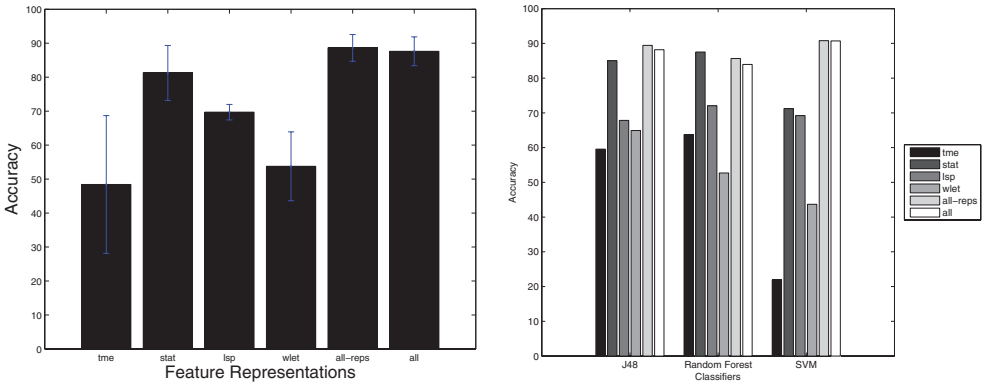
1. Introduction

The Australian Square Kilometer Array Pathfinder (ASKAP) will observe the entire visible radio sky, including previously unexplored regions of phase space, in a single day with sub-mJy sensitivity at a 5-second cadence. Because no other telescope in operation has those capabilities, ASKAP has the potential of advancing significantly the study of known transients and variables, while also enabling the discovery of new objects and object classes. The Variables and Slow Transits (VAST) survey science project of ASKAP is focused on the development of new algorithms for the detection of transients with time-scales as short as 5 seconds (Murphy & Chatterjee 2009). Source types of interest include X-ray binaries, supernovæ, Extreme Scattering Events, Intra-Day Variables, novæ, and dMe flare stars, and RSCVn. Source classification is a prerequisite for scientific study of radio transients and variables.

The overall goal of our study is to evaluate state-of-the-art machine-learning methods for archival classification of VAST light curves. Because VAST has no existing counterpart with data to use for empirical evaluation, we simulate light curves for each of the sources discussed above plus background sources, and study performance using different classifiers, observing strategies, signal-to-noise ratios, and light-curve characterizations.

Here we present just a summary of results using a daily observational strategy (VAST Wide; Murphy & Chatterjee 2009) which observes with an r.m.s. of 0.5mJy. Our results show that we achieve approximately 90% classification accuracy using a Support Vector

† Presented on behalf of U. Rebbapragada by K. Lo



(a) Accuracy by feature representation

(b) Accuracy by classifier and feature representation

Figure 1. Classification accuracy.

Machine and a concatenation of different feature representations. These results and others will be published as a VAST Memo in early 2012.

2. Classifiers and Light-Curve Characterizations

We selected standard classification algorithms that have proved successful in other light-curve classification tasks (Richards *et al.* 2011 and Wachman *et al.* 2009). Specifically, we evaluated Support Vector Machine (SVM; Cortes & Vapnik 1995), Decision Tree (J48; Quinlan 1986), and Random Forest (Breiman 2001) classifiers using implementations provided by the Weka data mining package (Hall *et al.* 2009). We have also worked with other types of classifiers, including probabilistic classifiers such as Naive Bayes and Logistic Regression. However, we found that SVMs, Decision Trees and Random Forests produced superior results on these data.

Machine-learning methods for classification presume the existence of a structured data set, where each example is a vector of "features." Real light-curve observations may not meet this requirement because light curves may contain different numbers of observations taken at differing sampling rates. Thus, in a real setting, one must create representations of the data that meet these requirements.

Our first feature set extracts statistics from the flux measurements of each light curve. These are a subset of the "non-periodic statistical features" used by Richards *et al.* (2011) and include moment statistics (e.g., mean, standard deviation, skew, kurtosis), flux percentile ratios, and shape statistics. We refer to this feature set as *stat*. Our second feature set, *lsp*, extracts coefficients from the Lomb-Scargle Periodogram representation of each light curve (Scargle 1982). We actually extract power information from the top 20 frequencies. Our third feature set, *wlet*, extracts wavelet coefficients using the discrete wavelet transform (DWT).

From the original time-domain observations, the statistical and two frequency space characterizations, we create the following six feature sets for our experiments: *tme* (time-domain flux measurements), *stat, lsp, wlet, all-reps* (concatenation of stat, lsp, and wlet), and *all* (concatenation of *tme, stat, lsp* and *wlet*).

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3. Experimental Setup and Results

We simulated 200 400-day light curves per source type at signal-to-noise ratios (SNR) of 3, 5, 7 and 10 (each is a unit of standard deviation). For source types Intra-day Variables and Extreme Scattering Events, SNR is defined in relation to the source's quiescent flux. For all other (transient) source types, SNR is defined with respect to the source's peak flux. For transient source types, the event occurs at time 0.

Our first result, in Fig. 1, shows accuracy by feature representation, averaged across all other parameters (SNR and classifier). We measure accuracy using 10-fold cross validation. The results show that the time domain observations alone yield the weakest performance on average, and combining the feature representations (*all* and *all-reps*) yields the best performance.

Fig. 1 shows accuracy per classifier and feature, averaged across SNR. SVM seems to have the largest variability in performance, recording the lowest performance for the *tme* feature, but the highest performance for the *all-reps* feature set. For the higher-performing *all-reps* and *all* feature representations, the three classifiers perform similarly. We conclude that feature representation more strongly informs performance than classifier selection.

4. Conclusions

These results are part of ongoing work to estimate the classification performance of VAST data prior to the arrival of commissioning data from ASKAP's BETA. We have also studied the impact of different VAST observational strategies, and estimated classification performance per source type. We plan to publish those results along with the results in this paper in a VAST Memo in early 2012. Our future plans are to refine our methods and feature representations in order to optimize classification performance in the archival setting.

5. Acknowledgements

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