

Using AutoClass Artificial Intelligence Program to Classify SDSS and IRAS Asteroidal Data



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Current Asteroid Classification

Tholen Classification (1984)	SMASS Clasification (2002)
A widely used taxonomy	More recent, higher resolution (no albedo considered).
Based on spectroscopic measurements from Eight-Color Asteroid Survey (ECAS)	Based on the Small Main-Belt Asteroid Spectroscopic Survey (SMASS)
Original formulation based on 978 asteroids	Survey included 1447 asteroids
14 types with majority falling into 1 of 3 categories: C-group: dark carbonaceous objects S-type: silicate (stony) objects X-group: metallic objects	24 types in three main categories: C-group: carbonaceous objects S-group: silicate (stony) objects X-group: metallic

The Problem

With over 530,000 known asteroids the current classification system represents a data sample of less than 1% of the known population.

The huge size of existing data sets make it difficult or impossible to organize the available information in any useful way using traditional plotting and/or classification methods.

Relevance

Information obtained about asteroid stratification may help us better understand the processes by which the solar system was formed.

Part of NASA’s 2010 Science Mission Directorate: Goal: “Ascertain the content, origin, and evolution of the solar system, and the potential for life elsewhere.” Among the fundamental questions: What is the inventory of solar system objects and what processes are active in and among them? What are characteristics of small bodies and planetary environments that pose hazards and/or provide resources?

Autoclass

AutoClass essentially makes a guess, H , about the possible classes and its degree of belief, $P(H)$, in H . Each class described in H has a distribution of possible values for each attribute. AutoClass then begins to analyze the input attributes and comes up with some arrangement of them, E , based on the likelihood functions for each attribute (determined by the models chosen). From there a likelihood function $L(EH)$ is developed which describes the likelihood of some particular attribute arrangement, E , given the current guess, H . The joint probability $J(EH)=L(EH)*P(H)$, divided by the sum of $J(EH)$ for all possible H is called posterior degree of belief, $P(HE)$, in H given E . What we have is the degree of belief in H given a set of evidence E , Bayes Rule, describing how beliefs should change with evidence. By repeating this process over many guesses, AutoClass determines the most probable H . This is the classification.

Kirkwood Gap

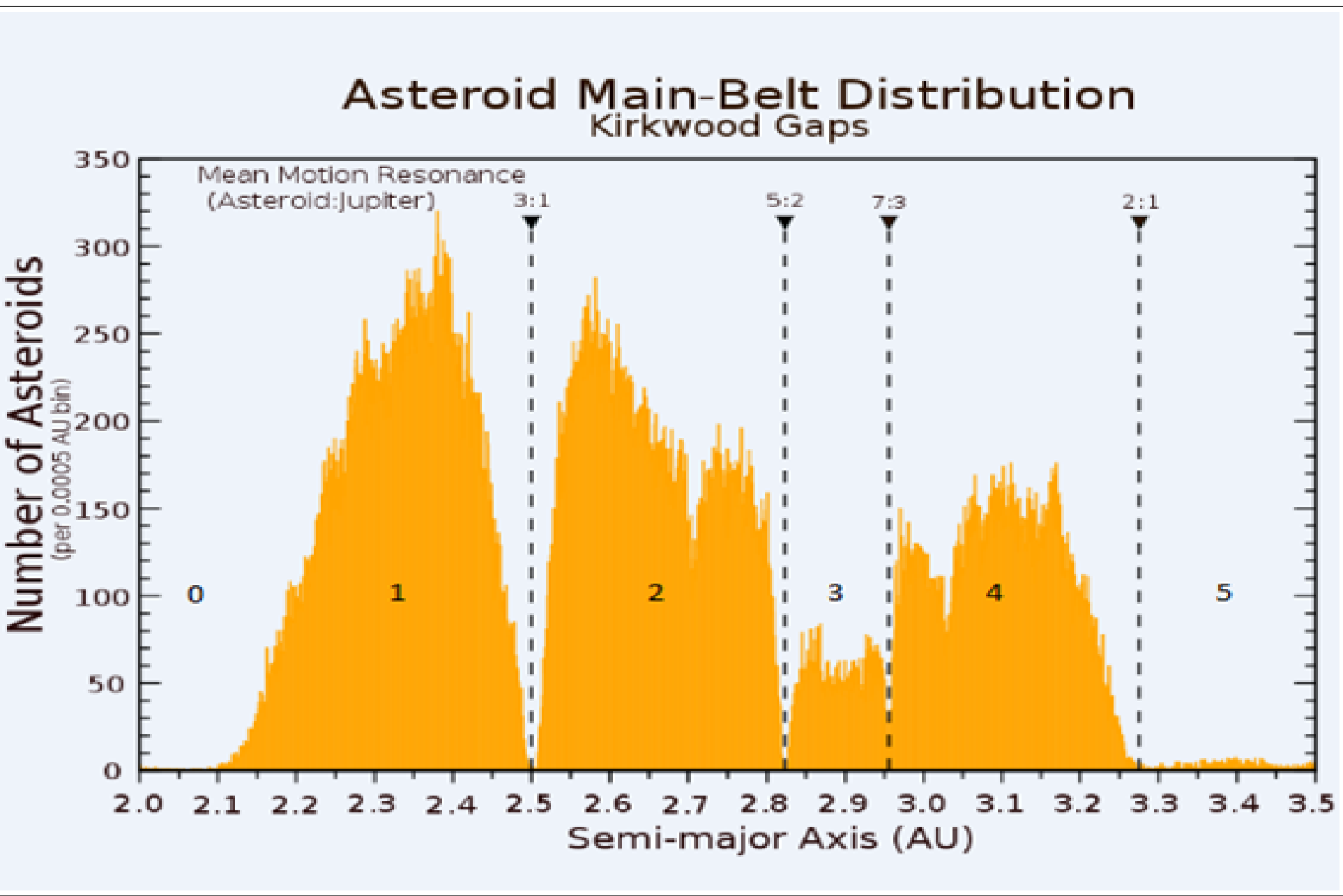


Figure 2: The Kirkwood Gaps are the vacant regions in the asteroid belt that are formed by Jupiter’s gravitational effect

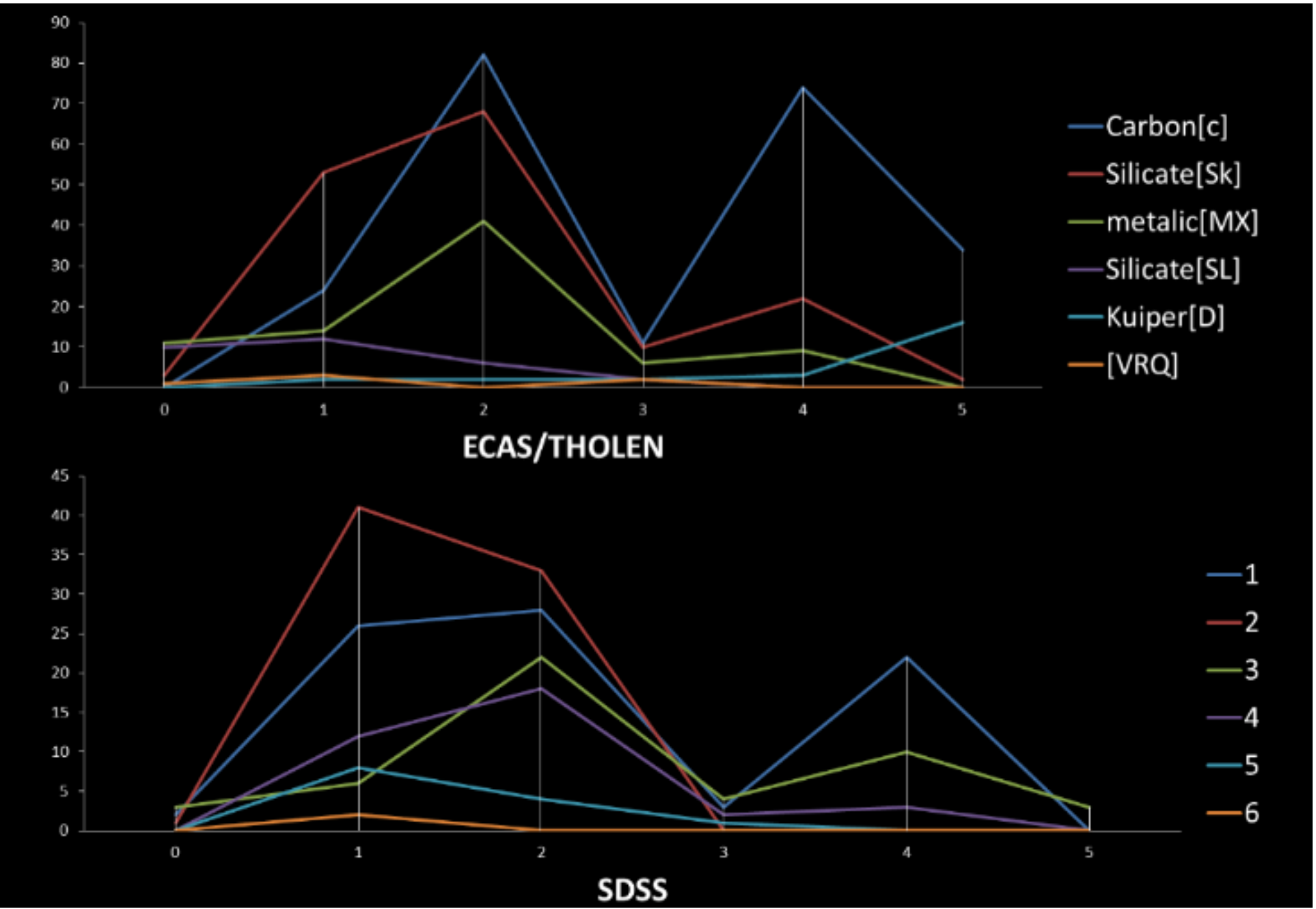


Figure 3: Top: The same technique was applied with ECAS and IRAS albedos. The distribution of the different classes throughout the Kirkwood regions of the asteroid belt. Bottom: 257 SDSS objects (not including albedos) and their distribution throughout the Kirkwood regions.

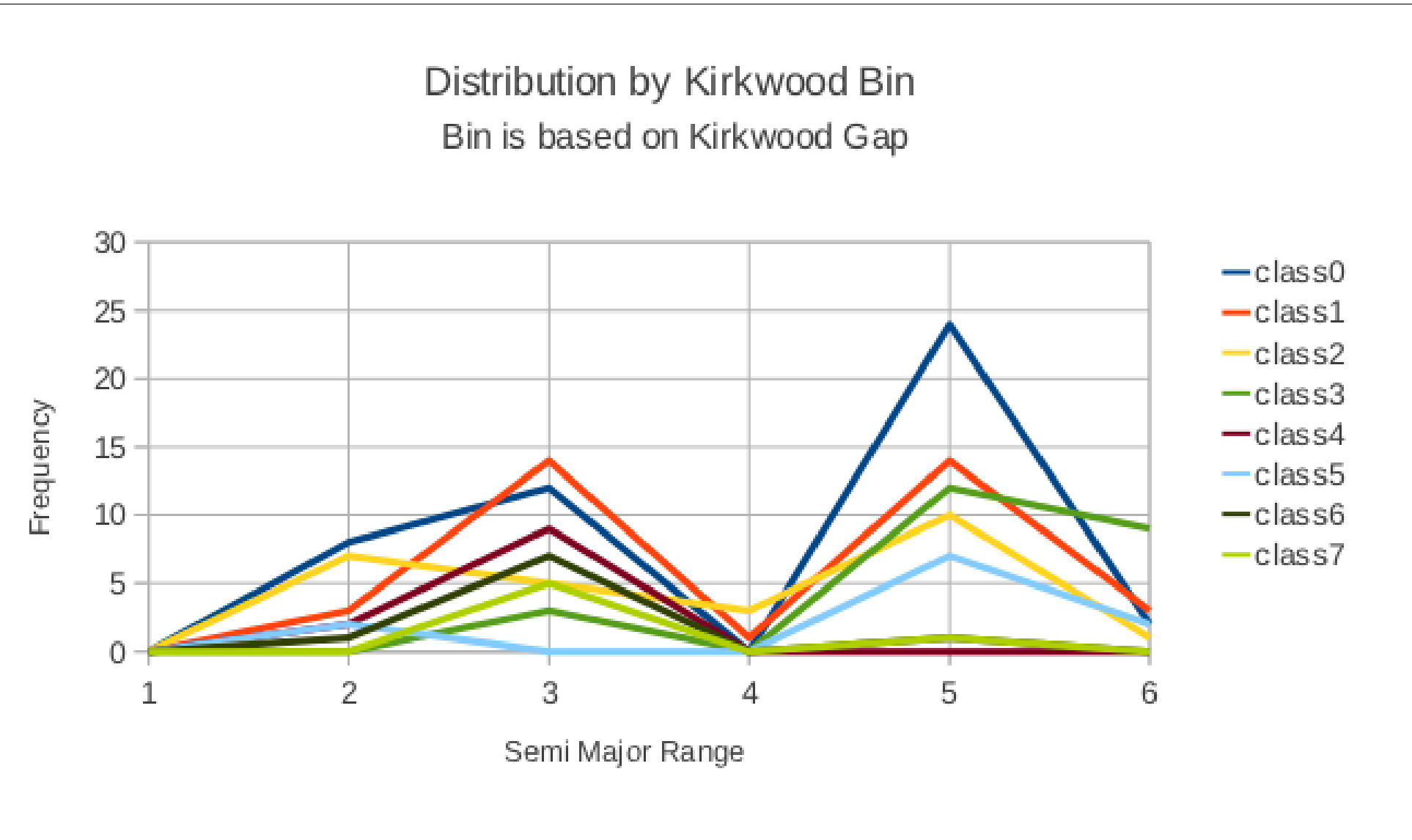


Figure 4: The graph above shows the regions for which the asteroids in SDSS and with IRAS albedos reside

Results

Our most interesting findings were unexpected: the albedos were labeled the least important factor. Upon examining the data, we found that the majority of the asteroids had relatively large semi-major axes. Since outer-belt asteroids are often primitive in nature with correspondingly low albedo, the majority of our asteroids likely have similar low albedo. The one class that has a moderately high albedo influence was the group with a shorter semi-major axis. Due to our success with these smaller data sets, we are optimistic about AutoClass’s ability to classify asteroids in SDSS and other large databases.