Detecting Asteroids with Neural Networks

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Outline

- What's the goal?
- What's the data?
- Getting started
- Building a feature set
- Building the neural network
- Training the network
- Results

The goal

Build and train a neural network to correctly identify asteroids in astrophotography data.

So...

How do we do it?

So...

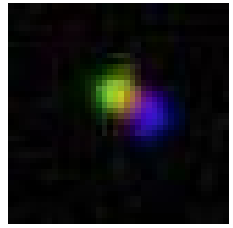
How do we *really* do it?

The data

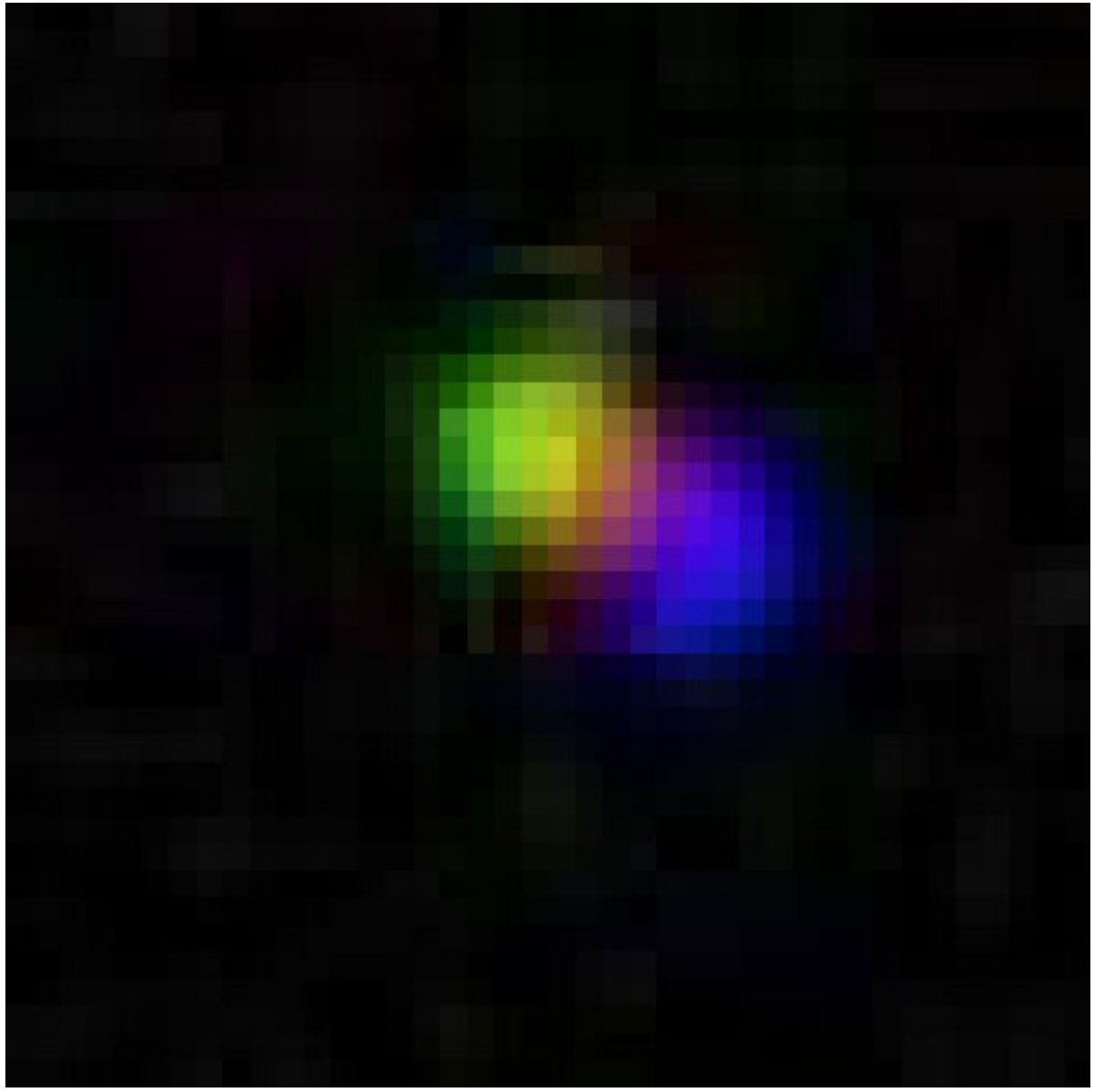
The Sloan Digital Sky Survey:

- "One of the most ambitious and influential surveys in the history of astronomy."
- Approx 35% of sky
- Largest uniform survey of the sky yet accomplished
- Data is freely available online
- Each image is 922x680 pixels

An example asteroid



An example asteroid

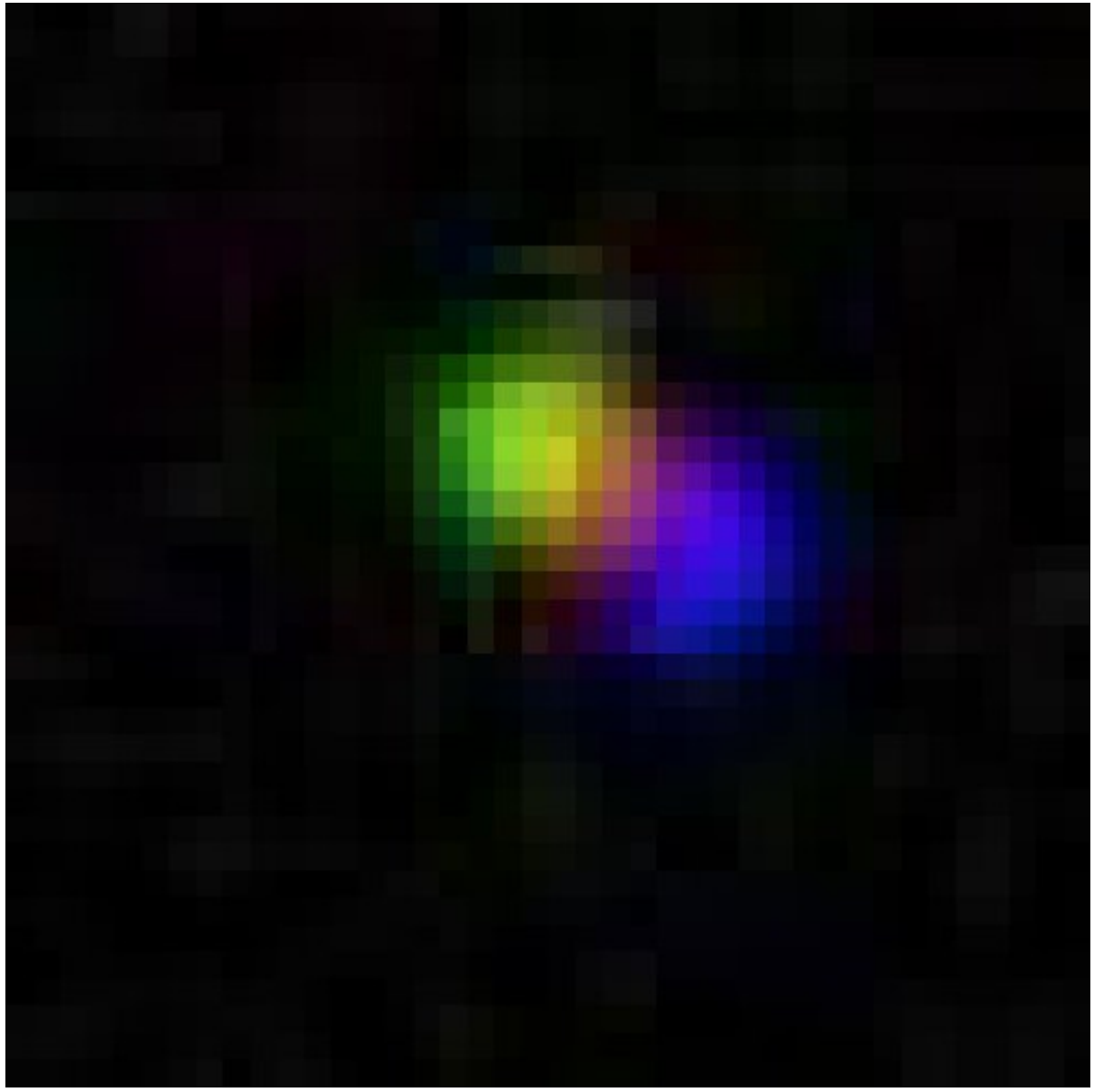


How does this work?

This exploits a property of CCDs:

- SDSS telescopes use five different filters
- They are not simultaneous
- Moving objects appear in different locations
- Always the same order

An example asteroid



Getting started

Getting the initial training data:

- Small tool to extract potential candidates from full-scale images
- Extremely naïve, approx 100:5 false positives to actual positives
- Very low false negatives (approx 1:1000)
- Incredibly slow (complex scan of 100Ks of potentials)
- Manual classification, somewhat slow
- Yields approx 250 valid items, 500 invalid items

The feature set

Good ideas for features:

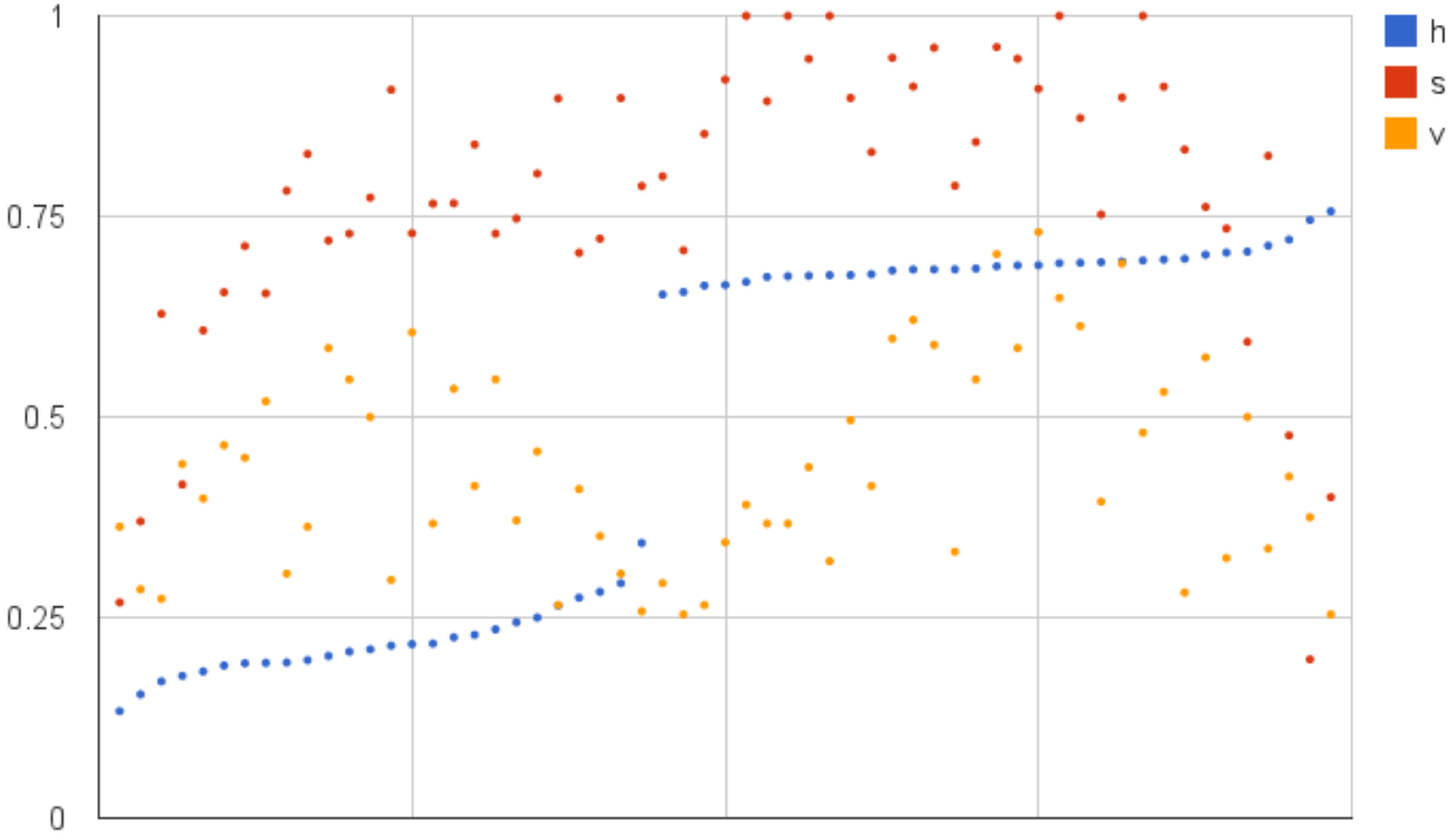
- Ratio valid hues to non-valid hues
- Best possible cluster collinearity
- Best possible average cluster distance

Feature: Ratio valid hues to non-valid hues

The goal here is to match the colors, a.k.a. "hues":

- First step: convert to HSV space
- For pixels in the valid value-spectrum ($0.25 < v < 0.90$)
- How many are within 2 standard deviations from an optimal value?
- What's the ratio to ones that aren't?

An example HSV plot

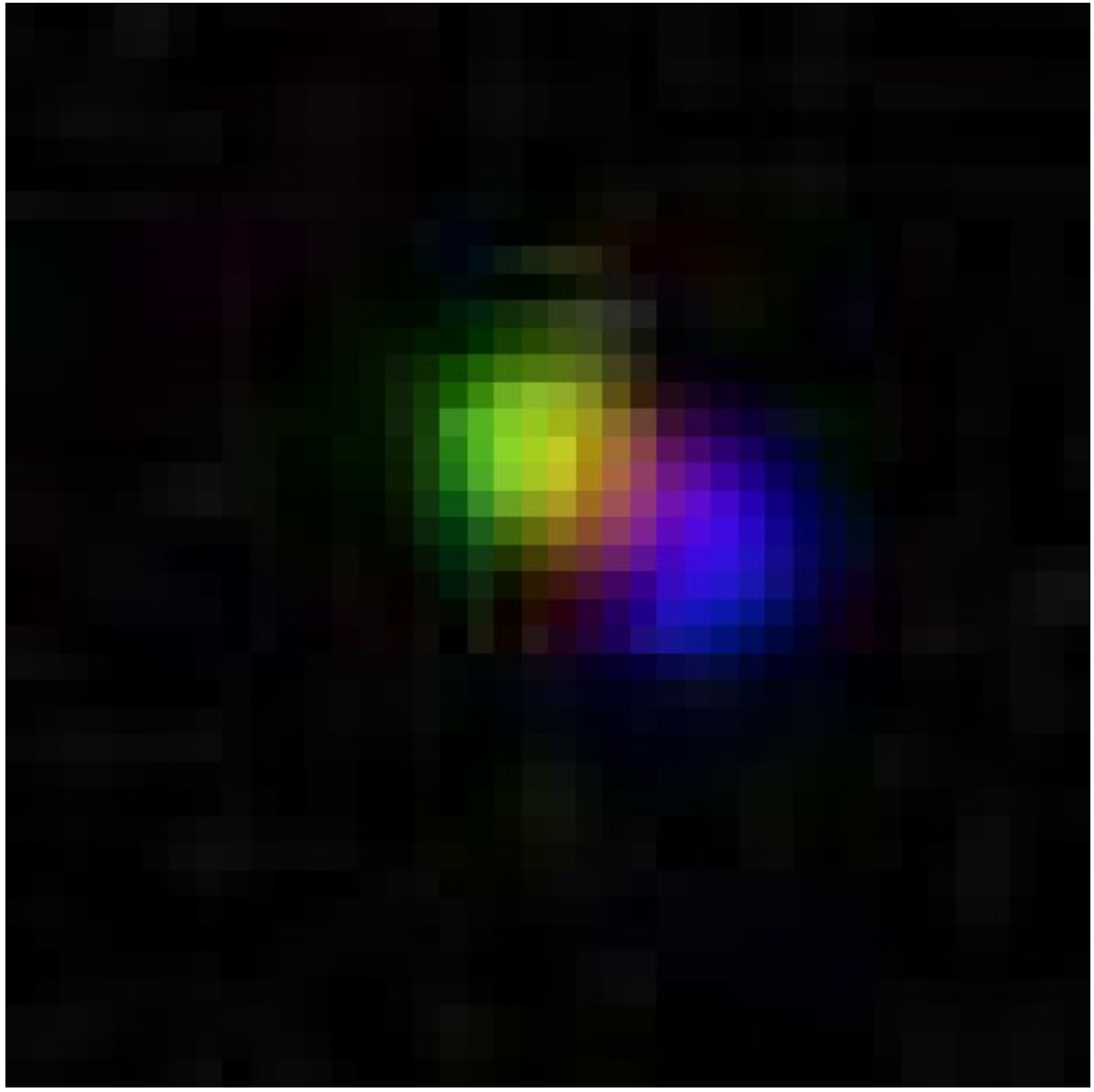


Feature: Best possible cluster collinearity

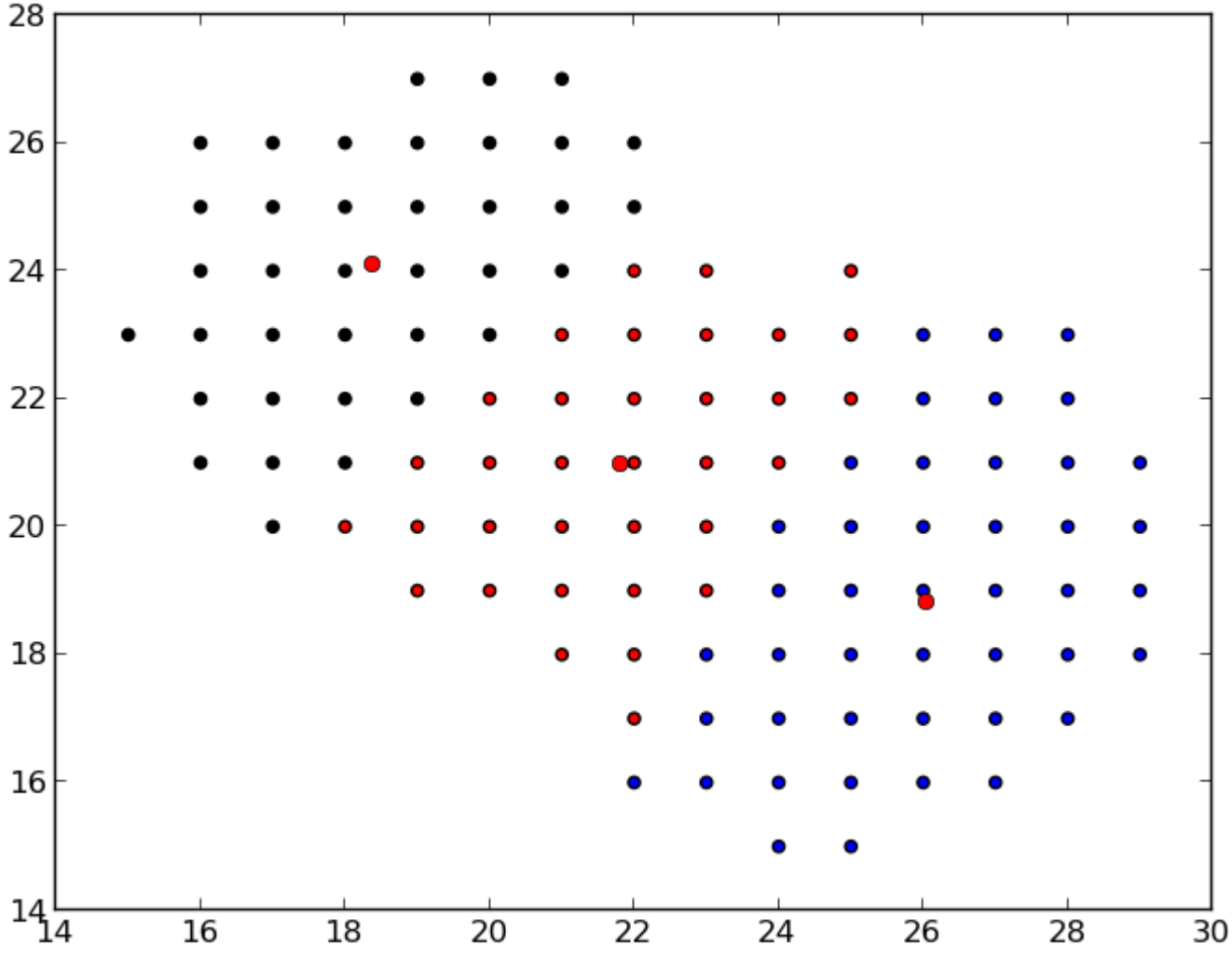
k-means clustering

- Using the valid hues from the previous feature
- Attempts to cluster n points into k groups
- Here, $k = 3$
- Produces three centroids

An example asteroid



k-means clustering of the same asteroid



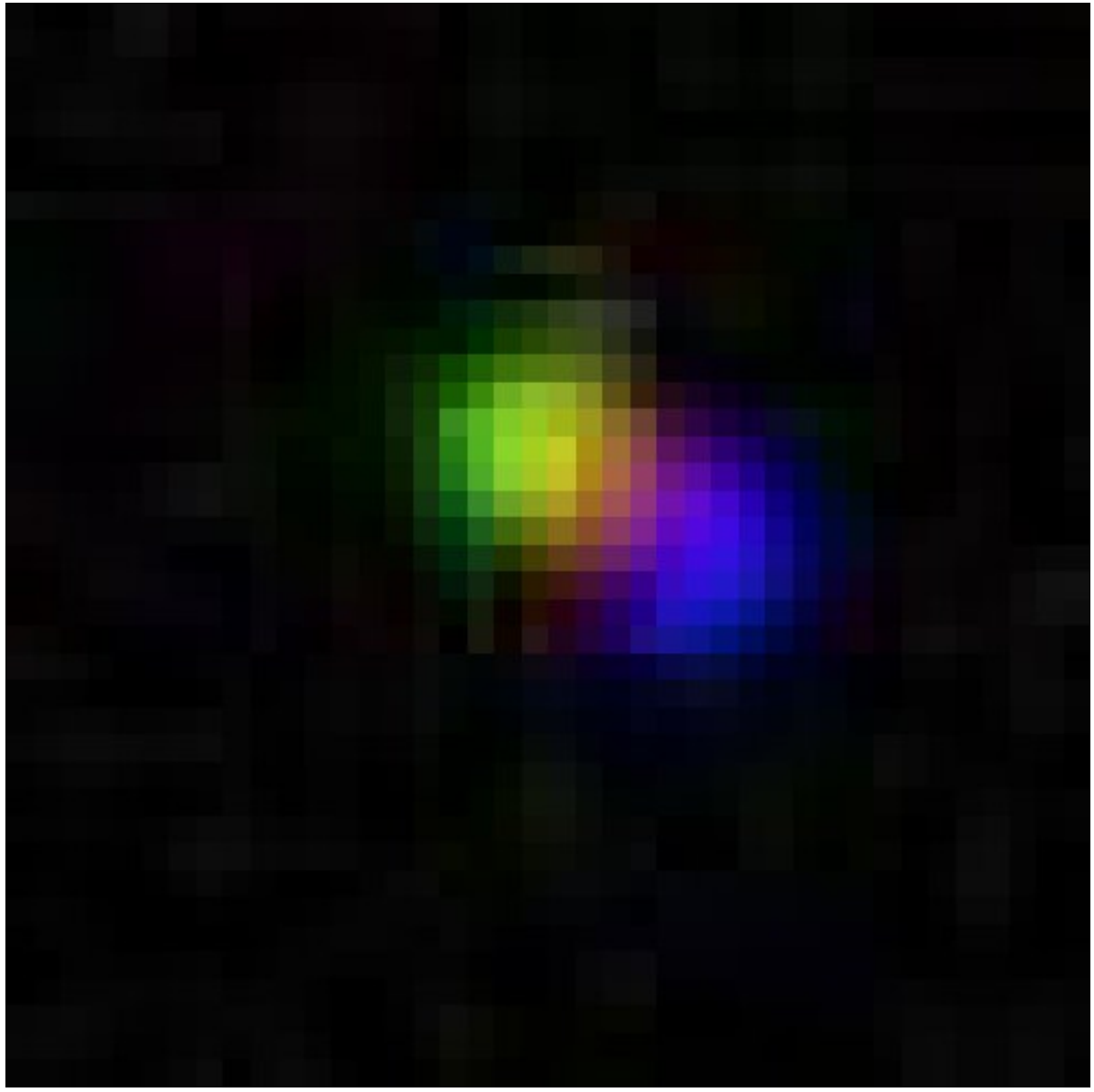
Feature: Best possible cluster collinearity

Collinearity:

- The property of a set of points which lie on the same line
- Iterate the k-means clustering approx. 20 times
- The resulting metric is the ratio between the actual collinearity and the maximum potential colinearity
- Given points a, b, and c:

$$colin = |(c.x - a.x) * (b.y - a.y) + (c.y - a.y) * (a.x - b.x)|$$

An example asteroid



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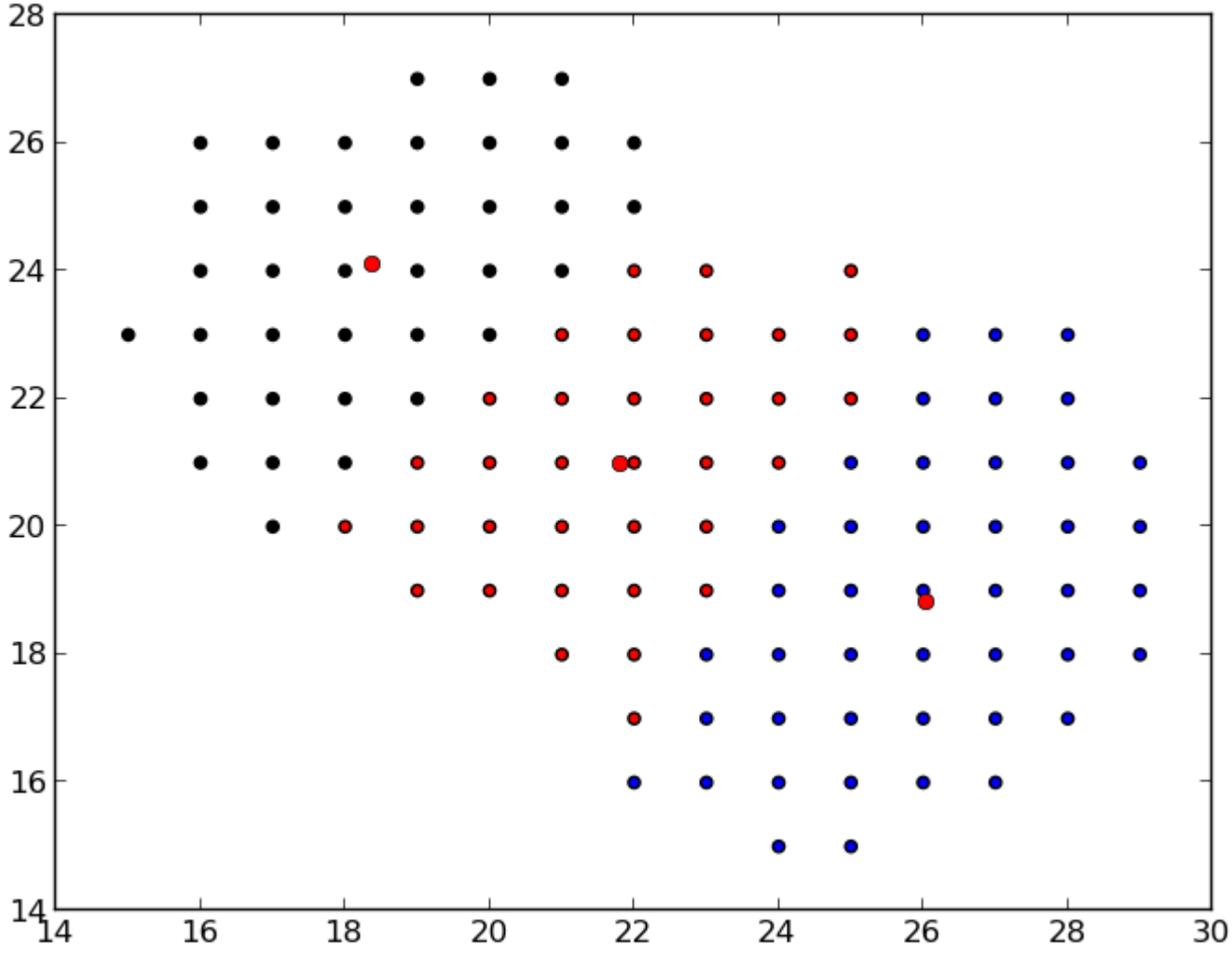
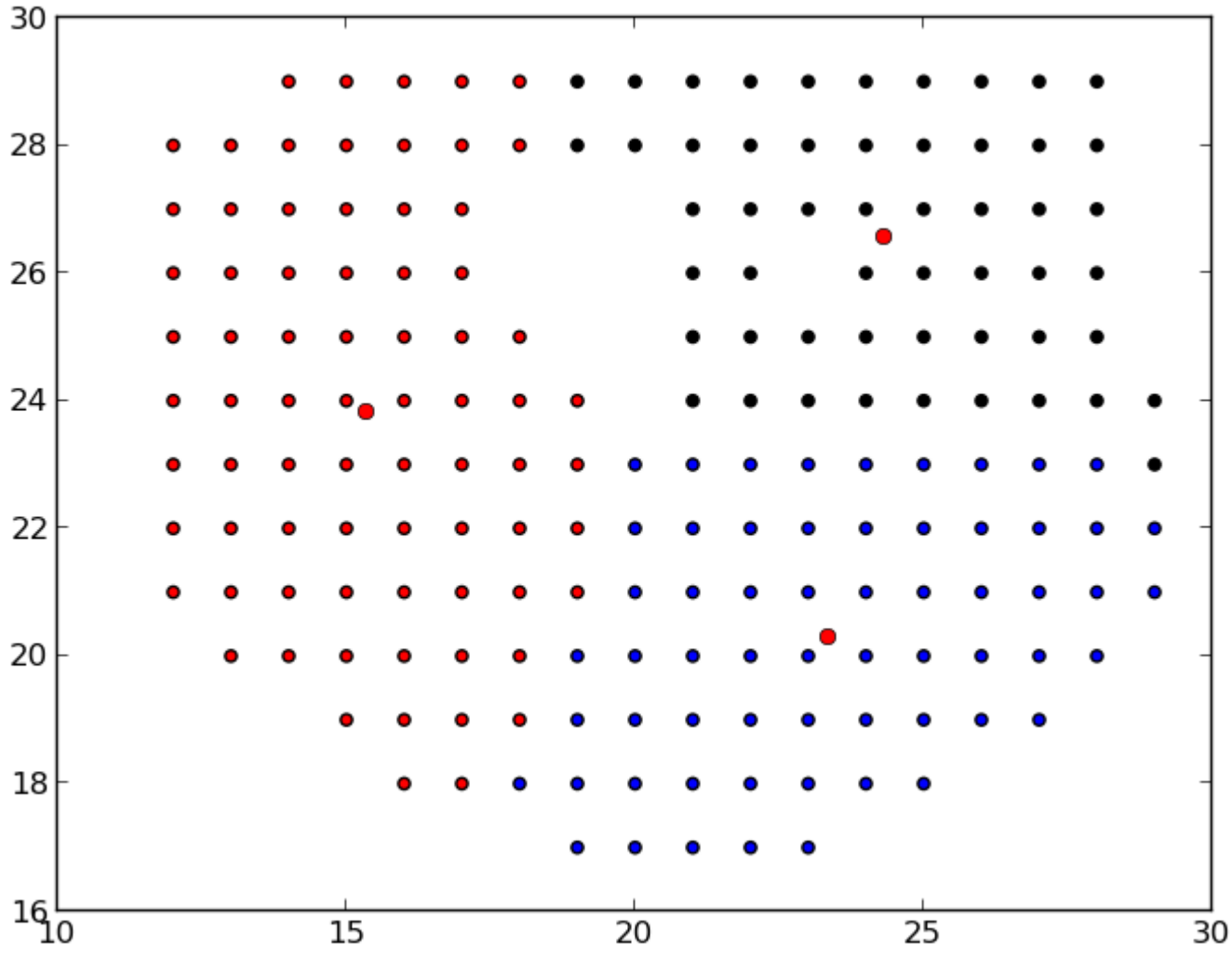


An example non-asteroid

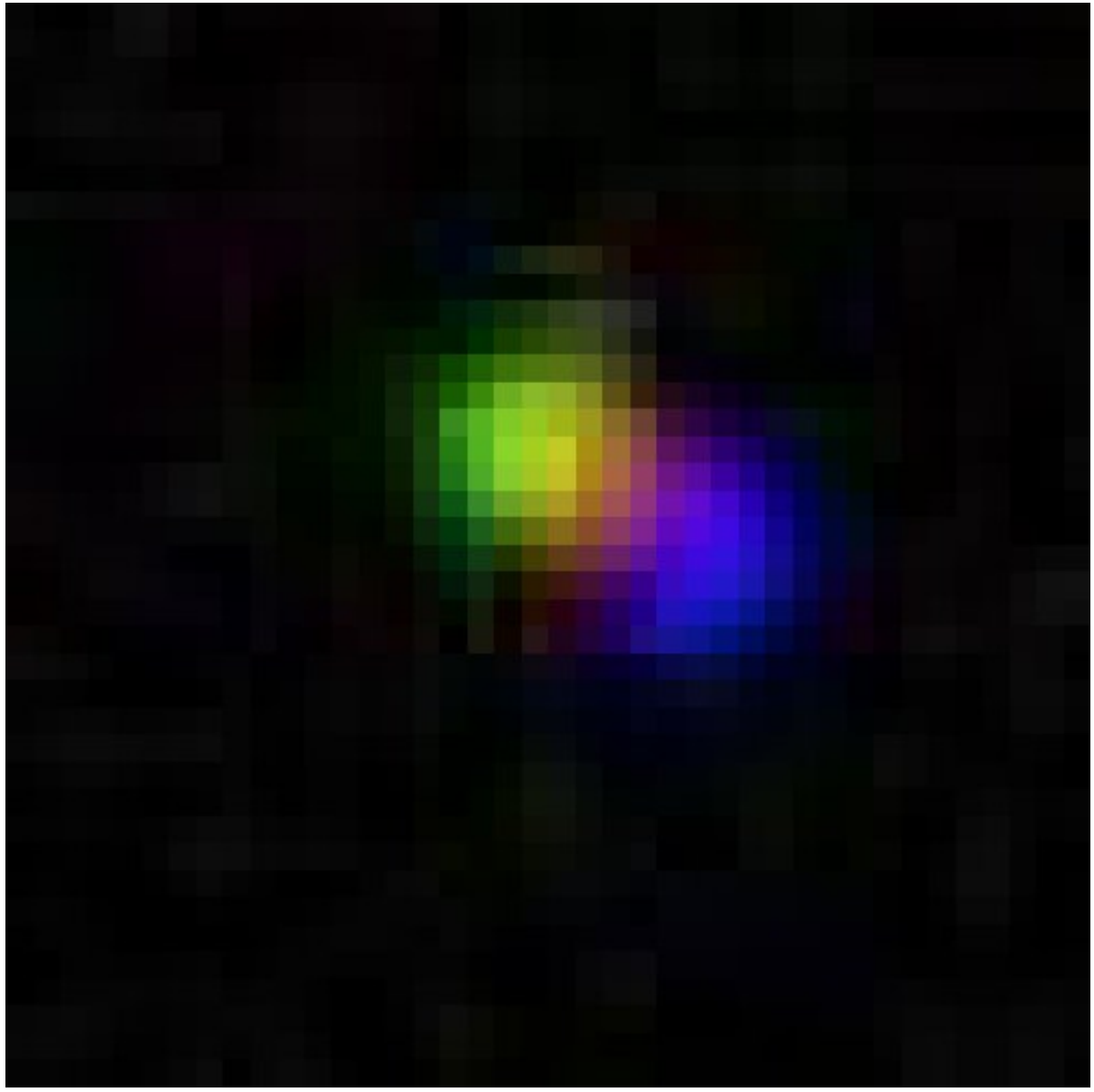
k-means clustering of the same non-asteroid



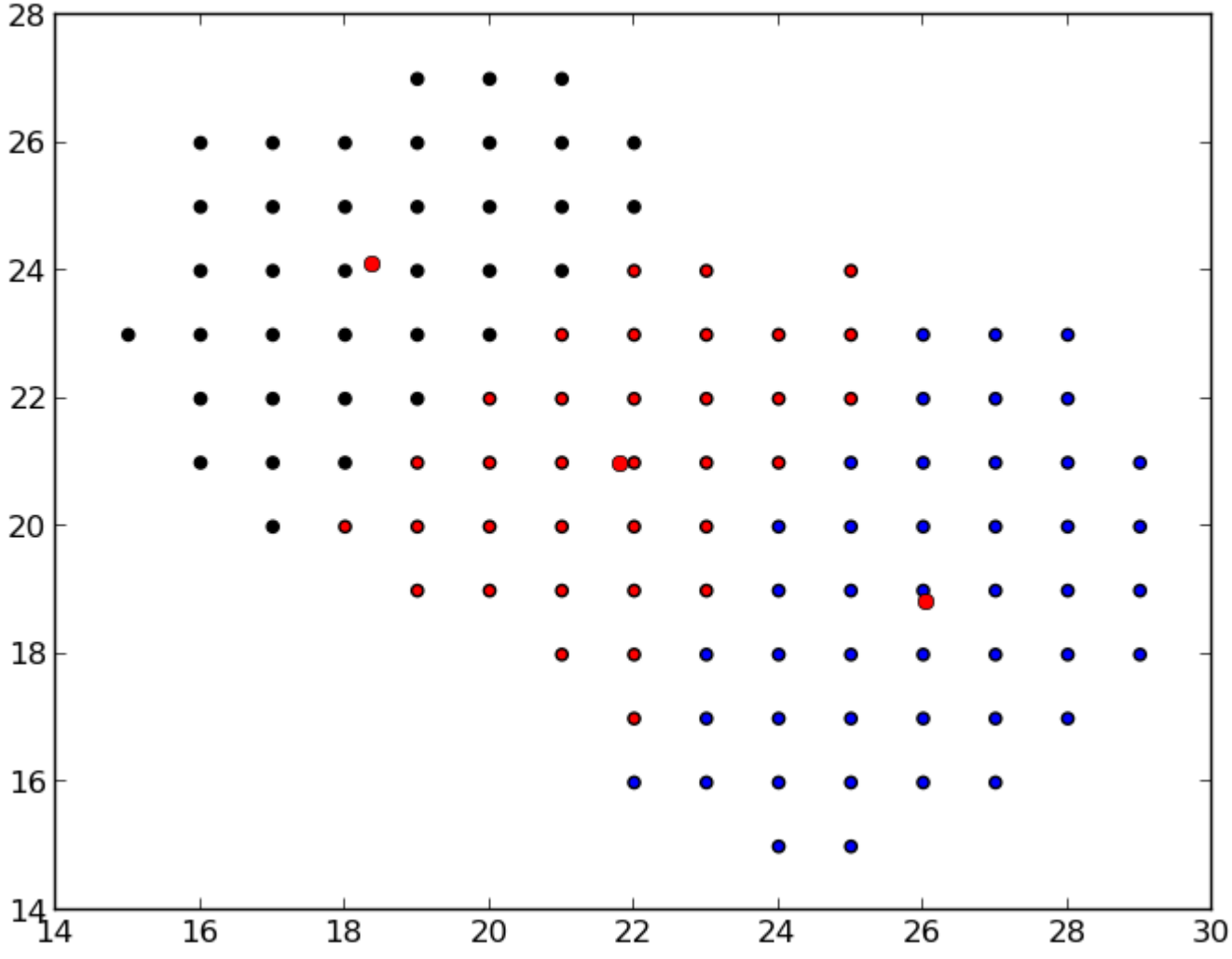
Feature: Best possible average cluster distance

- Using the same k-means clusters from the previous features
- What is the average distance from any point in a cluster to the center of the cluster?

An example asteroid

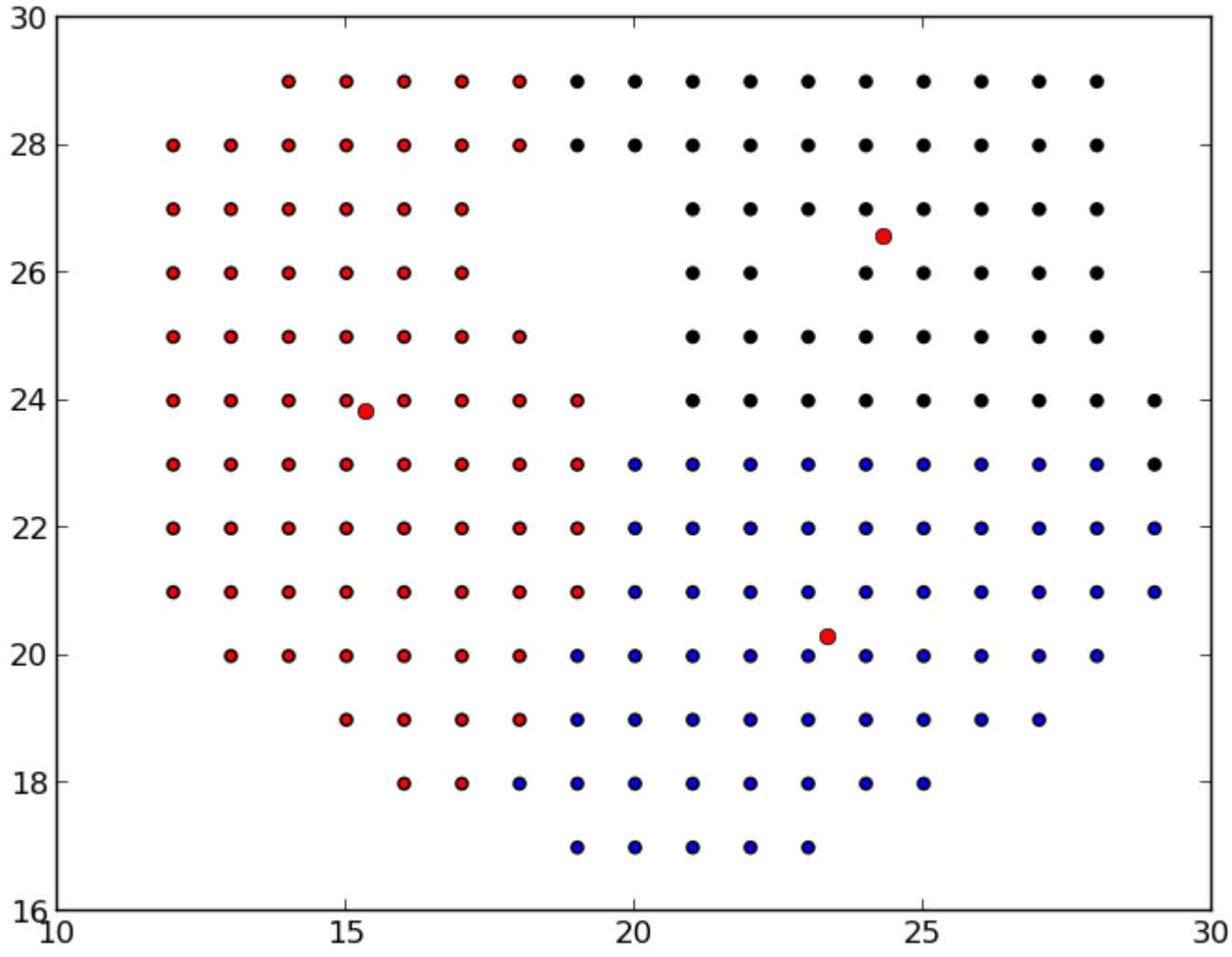


k-means clustering of the same asteroid



An example non-asteroid

k-means clustering of the same non-asteroid



A comparison of all three features

	Hue Ratio	**Collinearity**	**Cluster distance**
Asteroid	0.687	0.046	0.432
Non-asteroid	0.376	0.388	0.557

- We see that the for a valid asteroid:
  - The hue ratio is much higher
  - The colinearity metric is much lower
  - The mean cluster disance is smaller

Ok... where's the AI?

This type of classification is extrememly well suited for a neural network:

- We have a clear set of training data
- The output is either affirmative (1) or negative (0)
- Each of the input features can be resolved to a $0 \rightarrow 1$ metric
- There is a small amount of input features which can accurately define an item
- Neural network activation will be much faster than almost any algorithm we can come up with

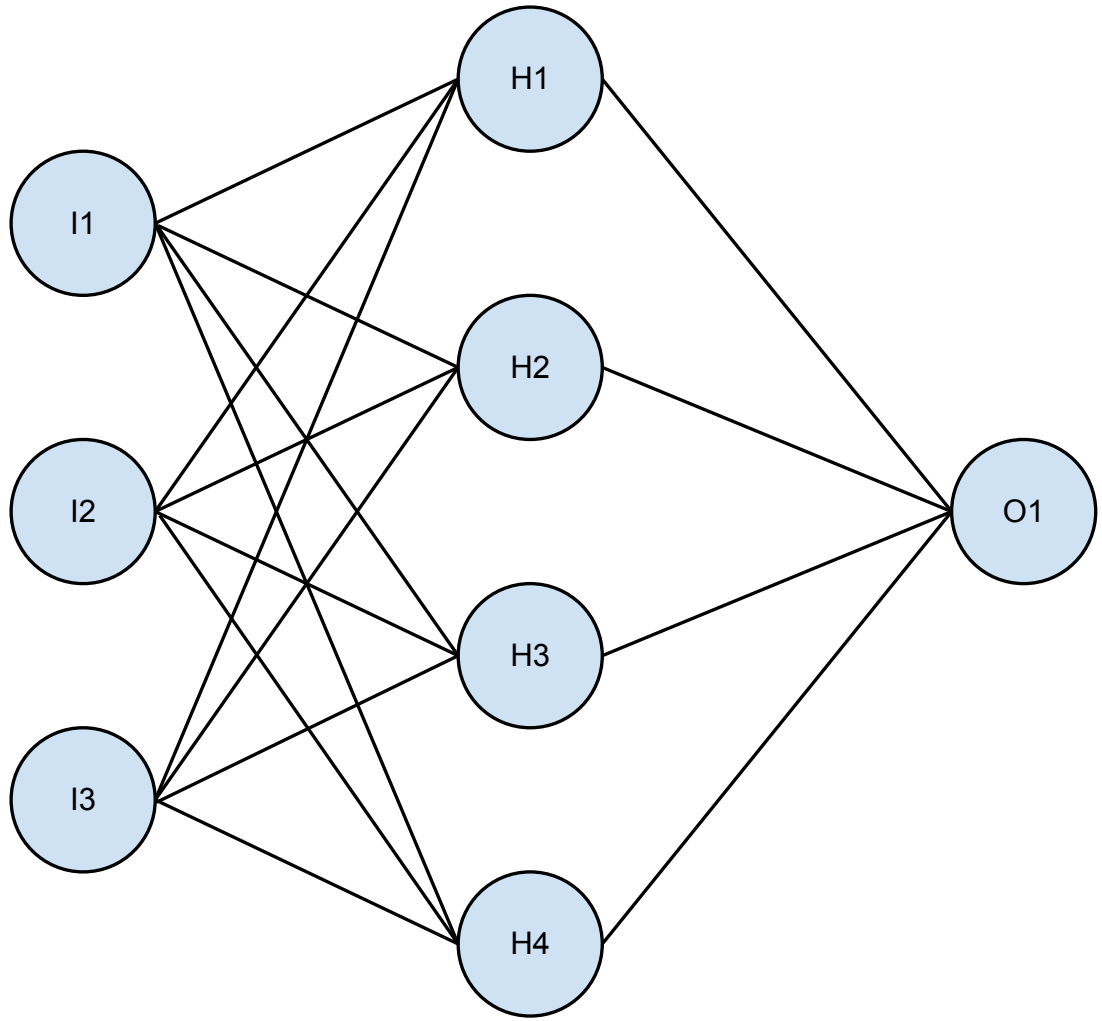
Building the neural network

The resulting neural network:

- Use supervised learning
- Uses a backpropagation trainer
- Three layers:
  - Input layer
  - Single hidden layer
  - Output layer
- Total of 8 "neurons":
  - 3 input neurons (hue ratio, collinearity metric, distance metric)
  - 4 hidden neurons
  - 1 output neuron (1 if valid asteroid, 0 if invalid)
- Learning rate of 0.01, momentum of 0.99

Building the neural network

The resulting neural network:



Training the network

- Approx 250 valid items
- Approx 500 invalid items
- Trained for 5,000 iterations
- Took approx. 3 hours
- Probably could have gotten by with less iterations

Results

Trial	Found Valid	Actual Valid	Total	False positive
Trial 1	8	5	190	37.50%
Trial 2	23	21	286	8.70%
Trial 3	54	46	955	14.81%

Results

Trial	Found Invalid	Actual Invalid	Total	False negative
Trial 1	182	182	190	0.00%
Trial 2	263	262	286	0.38%
Trial 3	901	892	955	1.00%

Conclusion

- Using a neural network allows us to do it faster, and more accurately
- Need to spend time coming up with good features for the data
- When paired with human validation, the process would become very quick and very accurate

References

- http://www.sdss.org/
- http://pybrain.org/
- http://en.wikipedia.org/wiki/Sloan_Digital_Sky_Survey
- http://en.wikipedia.org/wiki/Collinearity
- http://en.wikipedia.org/wiki/K-means_clustering