15-494/694: Cognitive Robotics

Dave Touretzky

Lecture 16:

Machine learning with scikit-learn

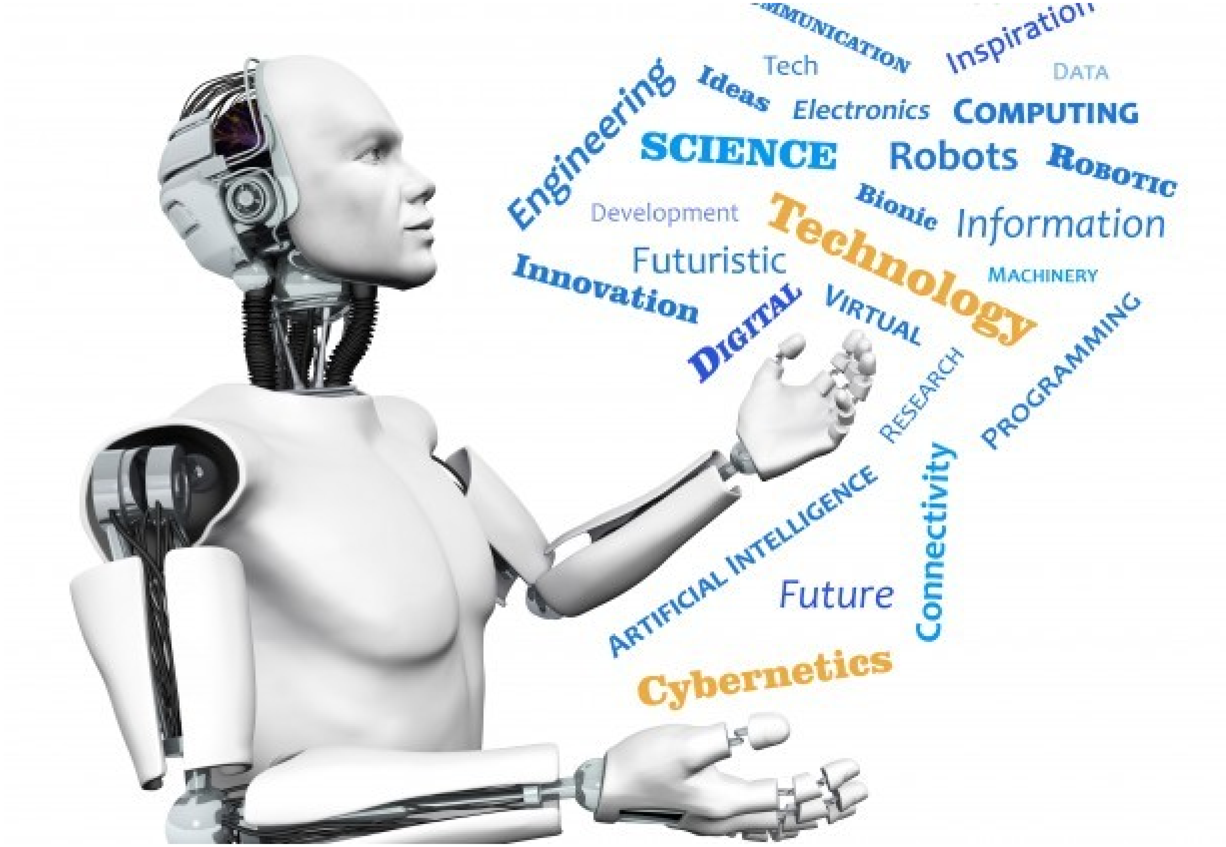


Image from http://www.futuristgerd.com/2015/09/10

Machine Learning

- ML is a branch of Artificial Intelligence.
- “Learning” does not mean human-like learning.
- It means extracting information from data. This has many uses in robotics.
- Types of learning algorithm:
  - Supervised (labeled data)
  - Unsupervised (unlabeled data)
  - Reinforcement

scikit-learn

- Open source collection of machine learning algorithms implemented in Python.

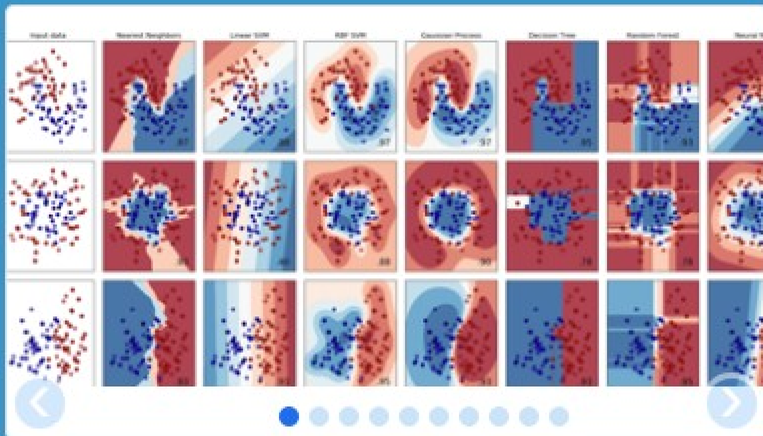
- Documentation at scikit-learn.org

- Installed on the lab machines:

```
import sklearn
```

Home Installation Documentation Examples

Google Custom Search



scikit-learn

Machine Learning in Python

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: SVM, nearest neighbors, random forest, ... — Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: SVR, ridge regression, Lasso, ... — Examples

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: k-Means, spectral clustering, mean-shift, ... — Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: PCA, feature selection, non-negative matrix factorization. — Examples

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning
Modules: grid search, cross validation, metrics. — Examples

Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms.
Modules: preprocessing, feature extraction. — Examples

Supervised Learning

- For each training point, there is a desired output value.

- Error measure: difference between actual output and desired output.
  - Example: sum-squared error

$$E = \sum \left(d_i - y_i\right)^2$$

- Learning adjusts the model parameters to reduce the error.

Unsupervised Learning

- Data points are unlabeled: there is no “correct” answer.
- Learning discovers structure in the data.
- Examples:
  - Clustering: finding categories.
  - Dimensionality reduction: finding key features and relationships between features. Useful for data compression.

Reinforcement Learning

- Used for *sequential decision problems.*
- Model is trained via a reinforcement signal that tells it how well it is doing.
- We don't tell it the right answer, just reward it when it does well.
- Example:
  - Learning to play a game by reinforcing wins. Program can learn by playing against itself.

Supervised Learning: Classification

- Desired outputs may be binary, or probabilities of class membership.
- Examples:
  - Tell “spam” from “not spam”.
  - Distinguish images containing cats from those without cats.
  - Recognize handwritten digits 0-9.

Supervised Learning: Regression

- Desired outputs are continuous, possibly vectors.

- Examples:
  - Interpolate values of a nonlinear function.
  - Predict stock prices.
  - Calculate inverse kinematics solutions for a non-linear robot.

Parametric vs. Non-Parametric Models

- Parametric models describe data using equations with a small number of parameters.
  - Example: Gaussian distribution.
  - Parameters are mean μ and variance σ

- Pros: compact representation; easy to test new data points.
- Cons: what if your data doesn't fit the equation?

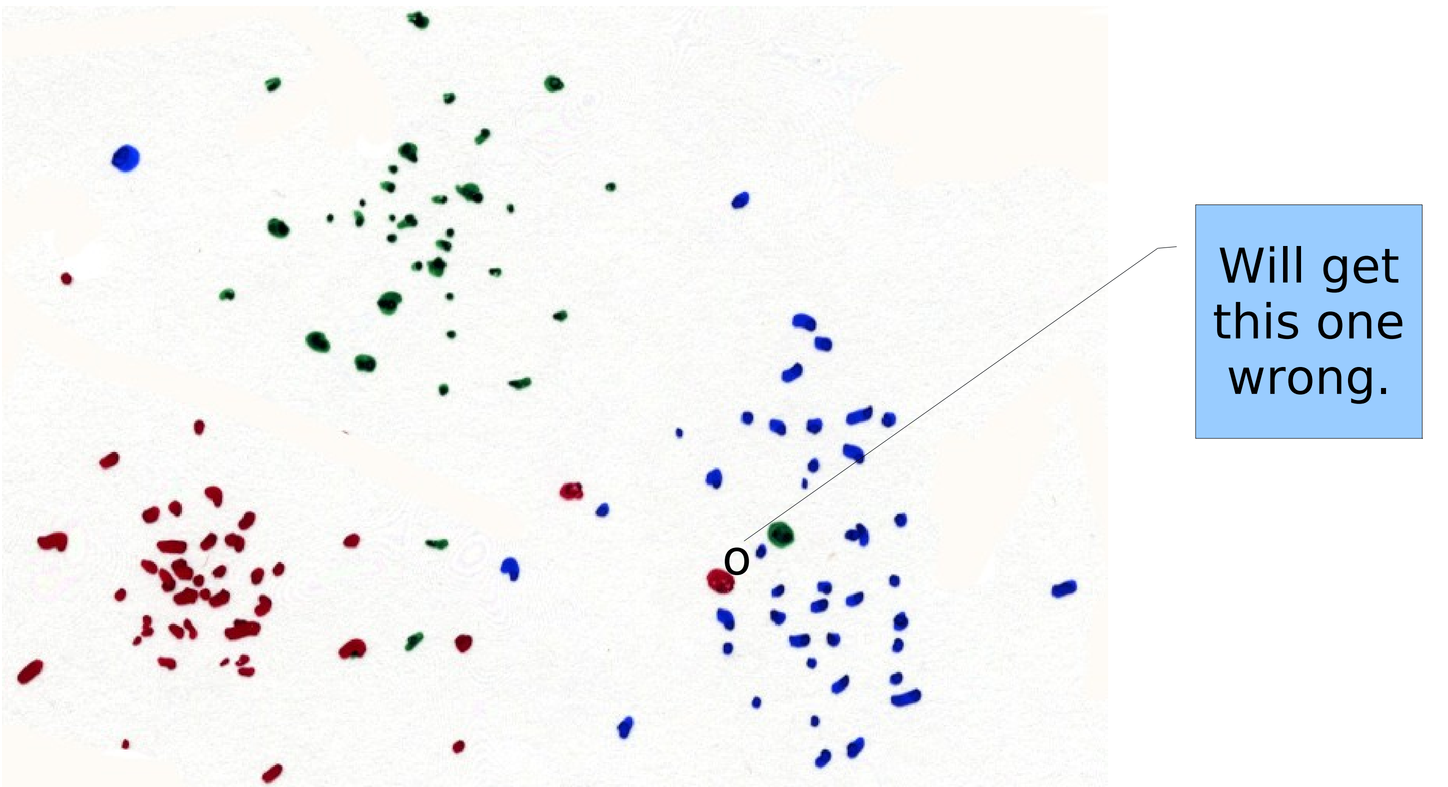
Parametric vs. Non-Parametric Models

- Non-parametric models don't make any assumptions about the distribution of the data. The data represents itself.
  - Particle filters are non-parametric models.

- Pros: “training” is instantaneous. Can represent arbitrary distributions.
- Cons: can take a lot of memory to store all the data, and classifying new points can be slow.

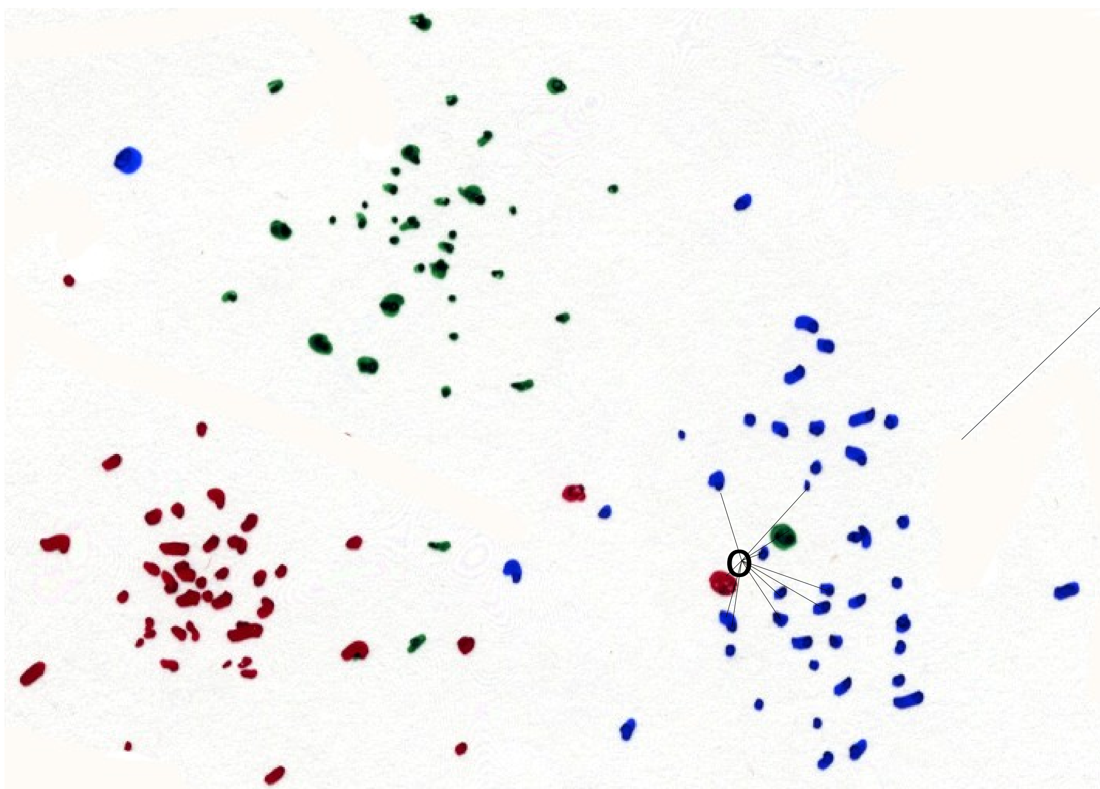
Nearest-Neighbor Classifier

- Simplest non-parametric classifier.
- Noisy data can be a problem.



k-Nearest-Neighbor

- Still a non-parametric classifier.
- Majority vote to find the correct class.

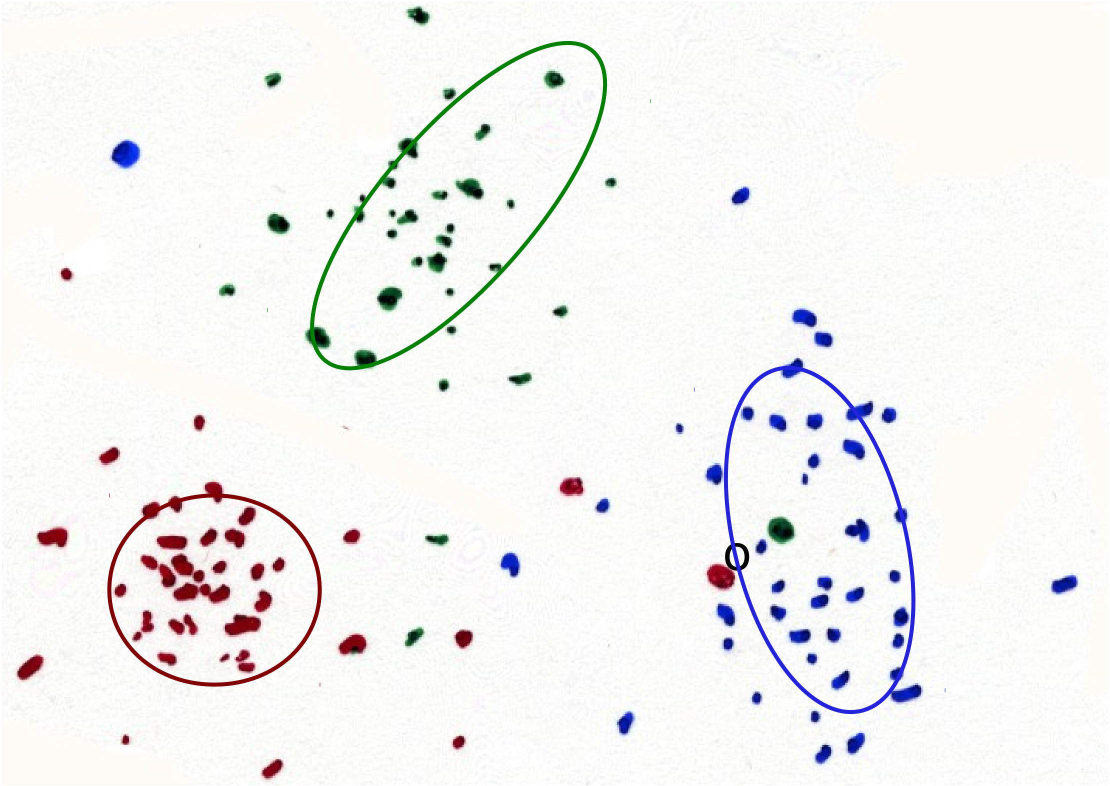


Majority vote: “blue”

Gaussian Mixture Model

- Parametric model: Gaussian distributions.

$$p(x \mid \mu, \sigma) = e^{\frac{-(x-\mu)^2}{\sigma^2}}$$



How do we find the correct values of the parameters?

Learning algorithm!

Sample Learning Problem: Color Classes

- Assume objects come in a small number of colors.

- We want to know what the colors are.
  - This is a clustering problem.

- Given a new object, we want to determine its color class.
  - This is a classification problem.

Training Data: RGB Values

Feature Space

- Three-dimensional feature space: RGB.

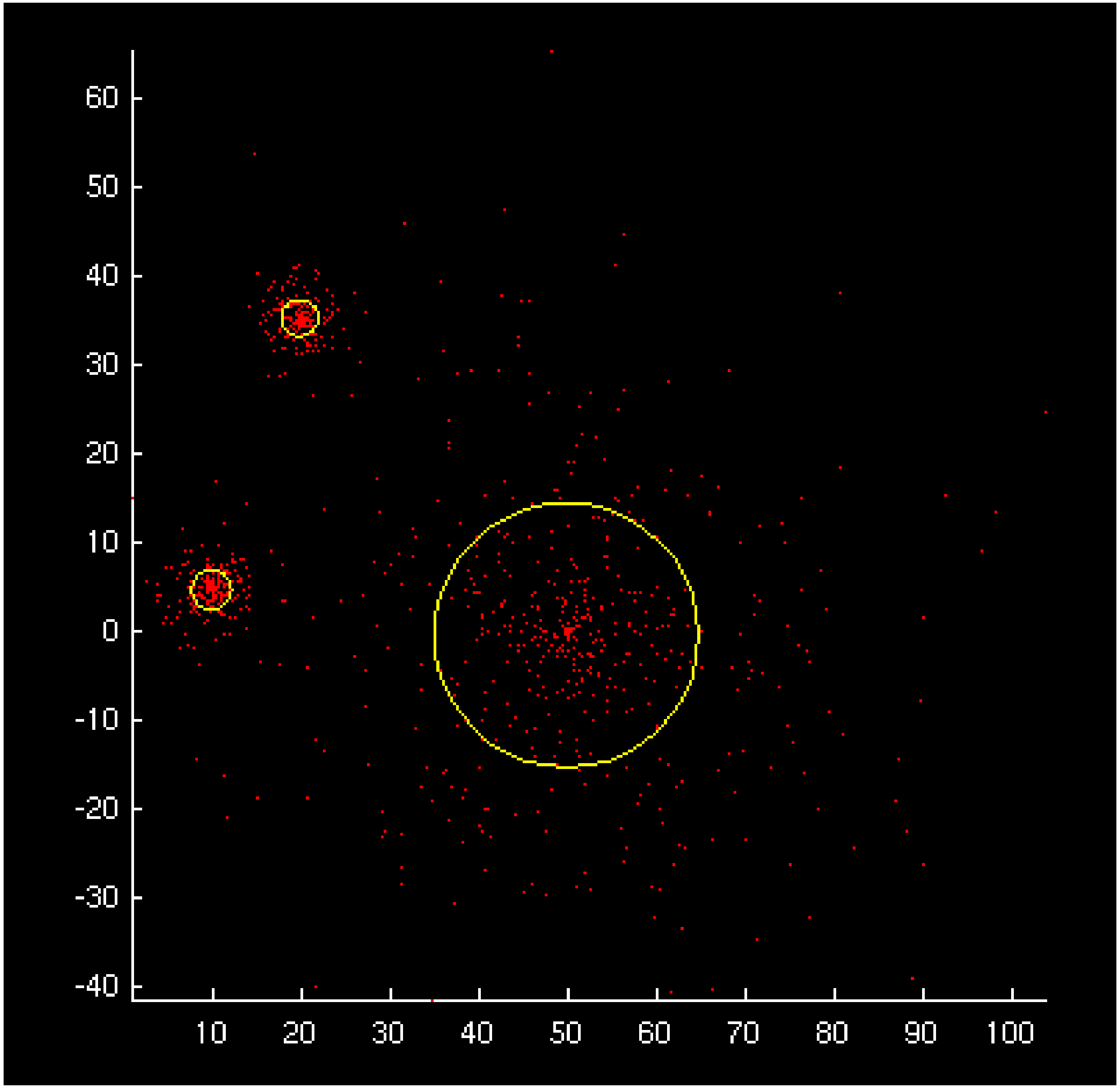
- 320 x 240 = 76,800 data points per image.

- Let's assume that each color class can be modeled as a gaussian distribution:
  - Mean color μ
  - Covariance matrix Σ

Expectation-Maximization Algorithm

- Unsupervised learning algorithm for finding clusters in data.
- Learns the μ and Σ parameters for a set of gaussians.
- You must guess the number of classes.
- Runs quickly but can get stuck in local minima.

E-M Clustering



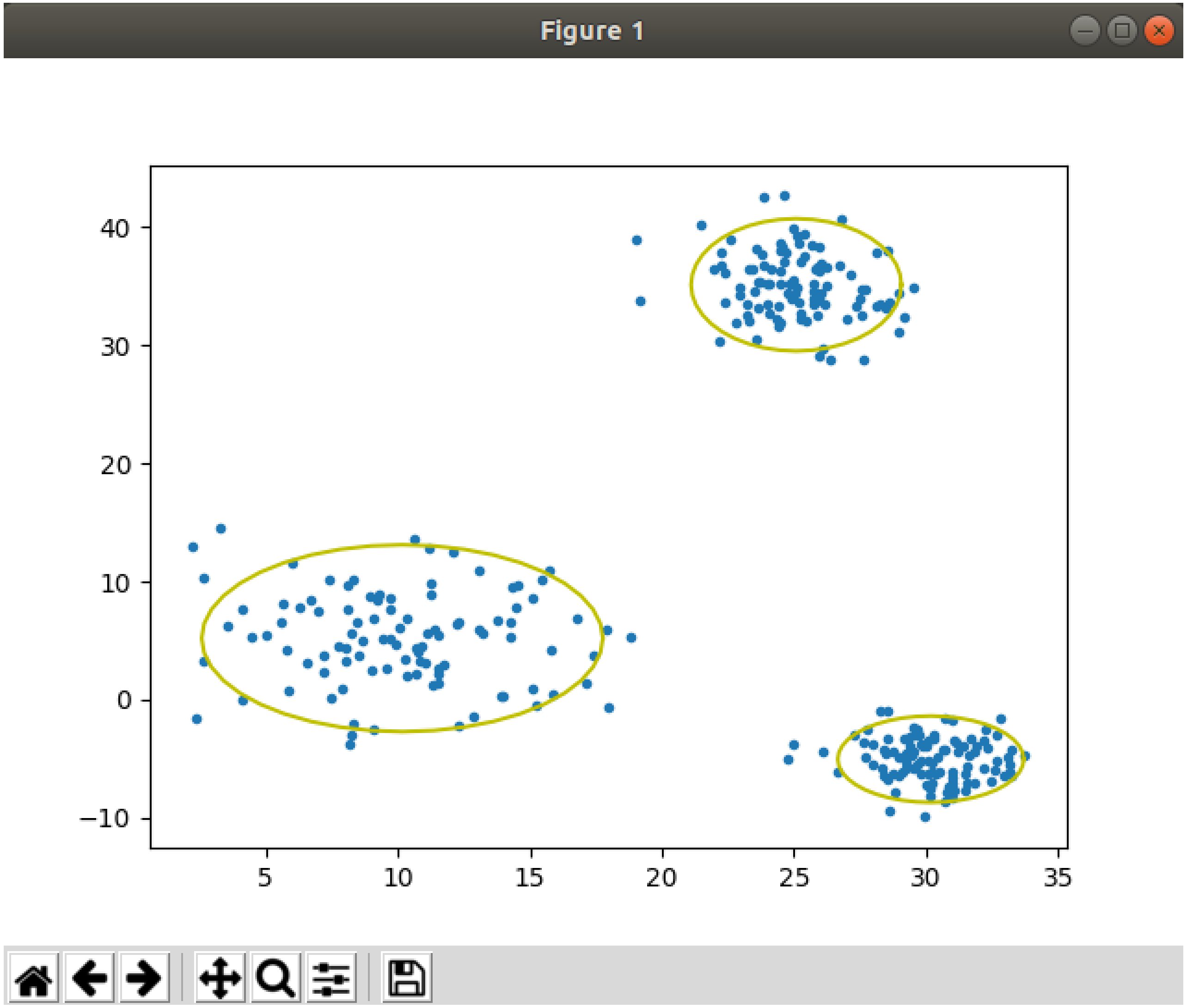
E-M Algorithm

- Expectation step:
  - For each point **x**, for each gaussian (μ_i,Σ_i), calculate the likelihood of **x** having been generated by the *i*-th gaussian: $P(\mathbf{x}|\mu_i,\Sigma_i)$.
- Maximization step:
  - For each gaussian, recalculate its mean and covariance μ_i,Σ_i based on the likelihood-weighted data points.
- Repeat for several iterations.

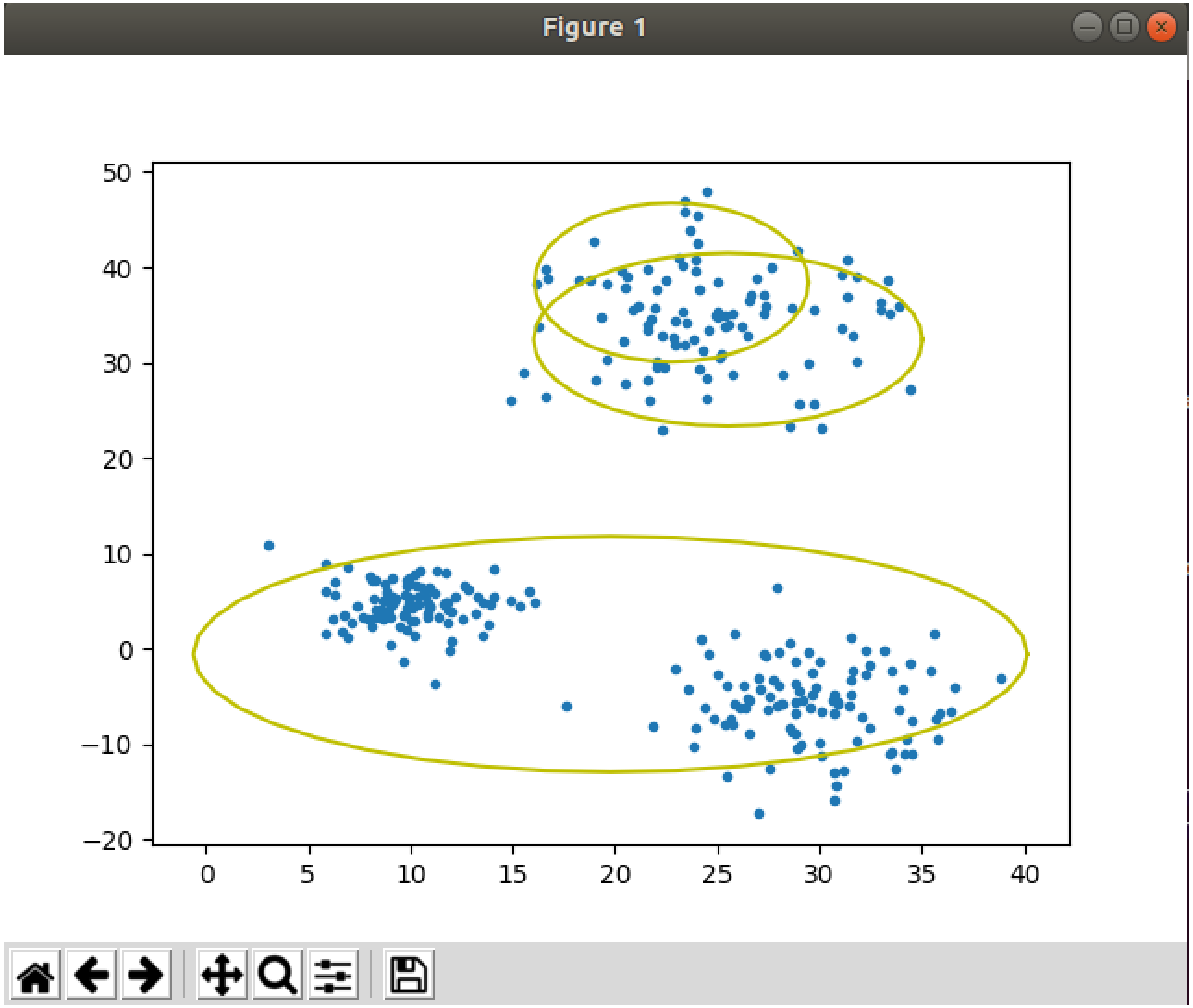
E-M in scikit-learn

```
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=7)
gmm.fit(data)
means = gmm.means_
covariances = gmm.covariances_



classes = gmm.predict(new_data)
```

emdemo.py



EM doesn't always succeed

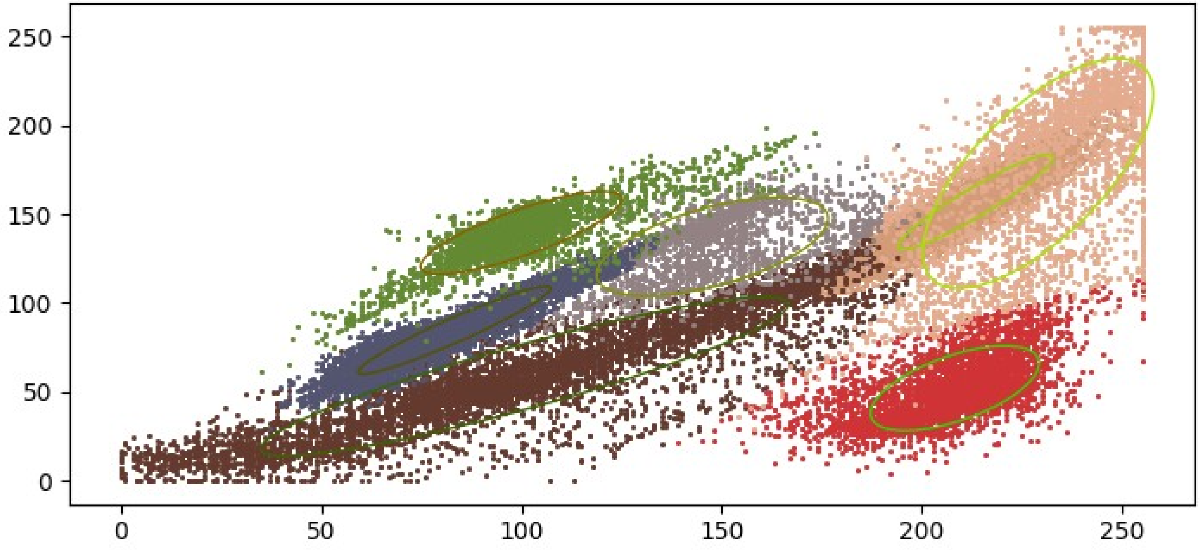


Color Classification: Visualizing the Result

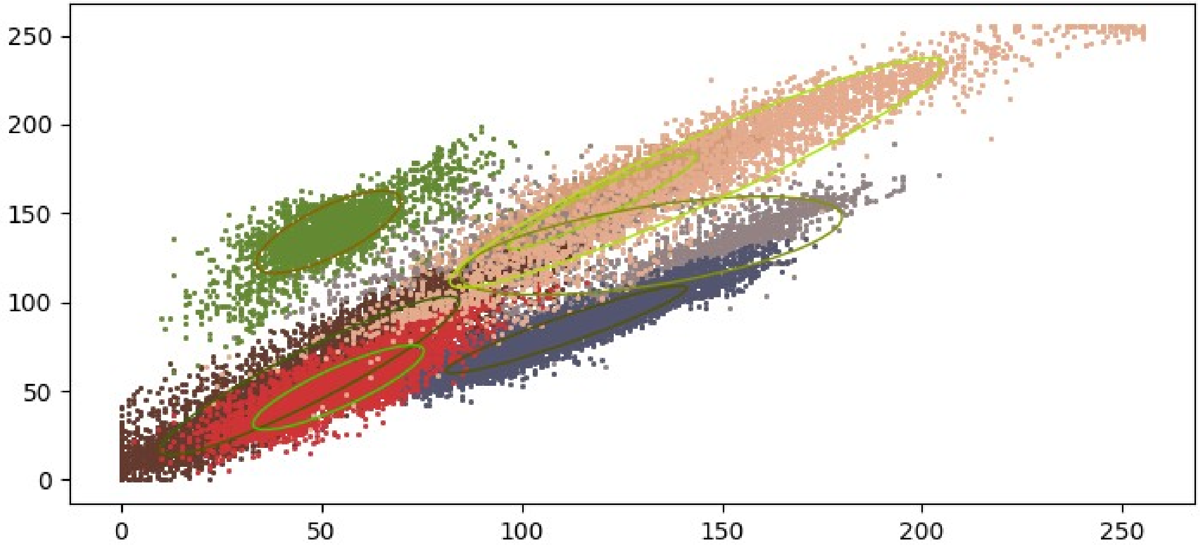
- Each color class is modeled as an ellipsoid in 3D space (RGB space).

- Too hard to plot. So instead:
  - Generate R-vs-G and B-vs-G plots.
  - Draw the ellipses in feature space determined by the covariance values.

Scatter Plots With Gaussian Ellipses



Red vs. Green



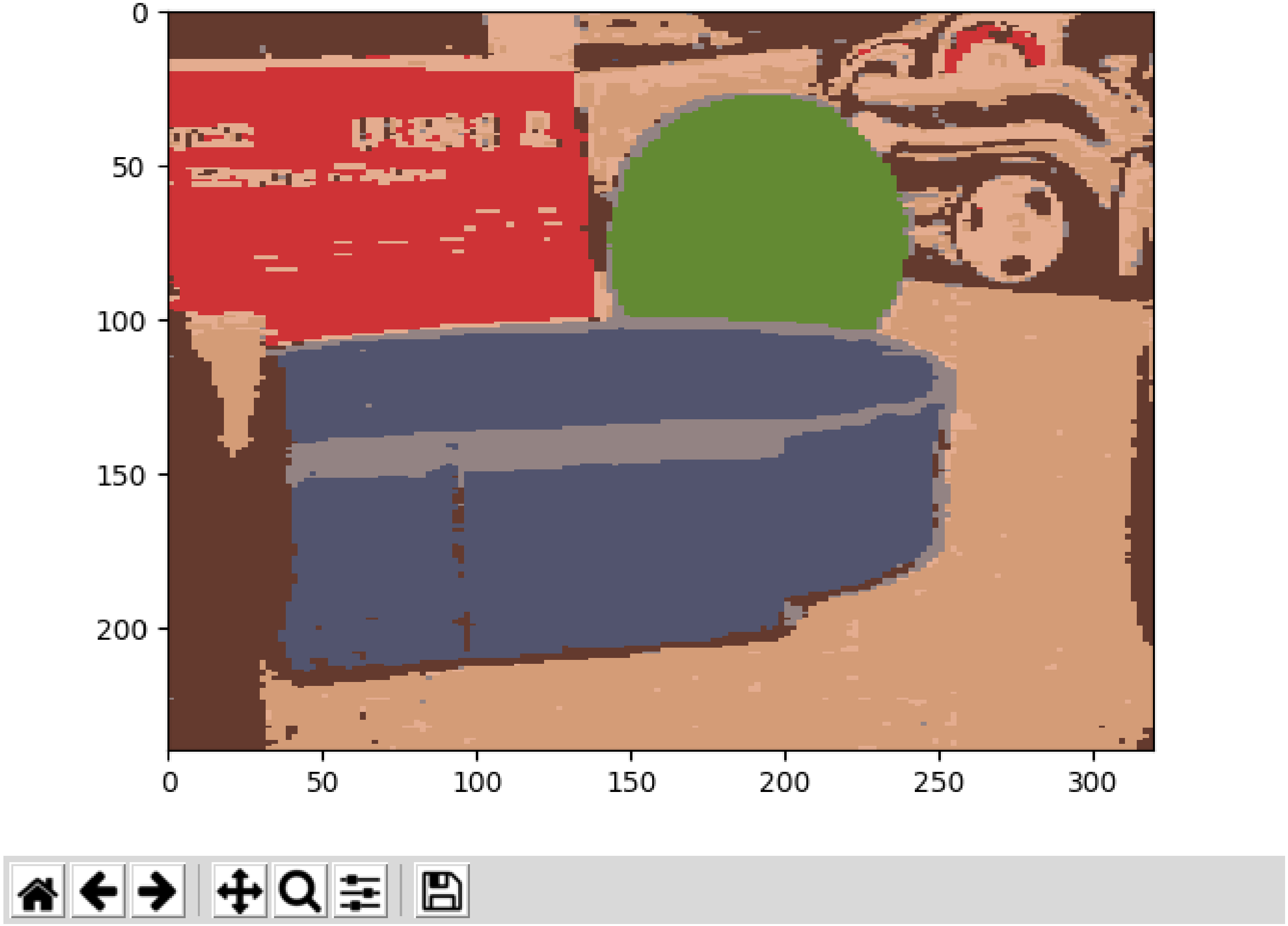
Blue vs. Green

Classification

- Once we've learned the color classes, we can assign a class to each pixel.
  - This gives us a color-quantized image.

- Can then use these color classes to classify new images the same way.

Classified Image



Refinements

- Can detect local minima by checking the density of points near the mean of the gaussian.
- Split/merge EM can reallocate gaussians if some are being wasted and others are spread between two clusters.
- BayesianGaussianMixture class in scikit-learn can infer the number of effective components.