



# Classification

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# Outline

- Introduction to supervised classification (labelled data):
  - Generative: Naive-Bayes
  - Discriminative: Logistic Regression
- Introduction to unsupervised classification:
  - $k$ -means
  - GMM

# Data Sets & Preprocessing

- **Dimensionality reduction:**

- PCA
- LDA

- **Data Sets:**

- **Training Set:** Train Classifier
- **Validation Set:** Hypeparameters (prevent overfitting).
- **Test Set:** Performance.

NB: Be careful-  
Splitting of data



# Performance

- Supervised:
  - confusion matrix
  - Accuracy
  - etc...
- Unsupervised:
  - GMM: likelihood
  - K-means: distortion

# Supervised Classification (Chap 4)

# Classification/Classifiers

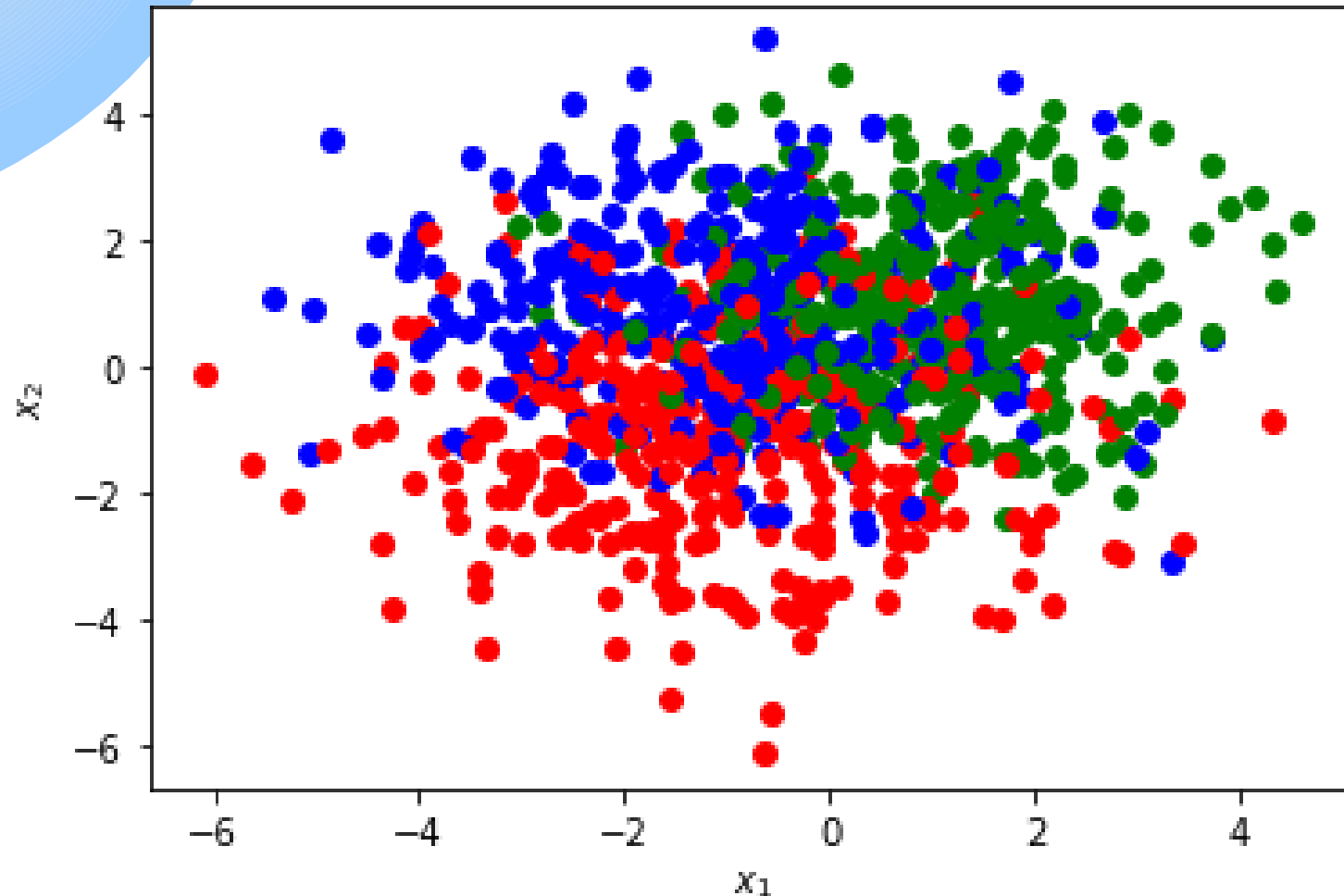
- Given  $\mathbf{x}$  assign to one of  $k$  classes:
  - $C_j, j = 1, \dots, k$
  - Assign prob  $P(C_j|\mathbf{x})$
  - $C^* = \operatorname{argmax}_{C_j} P(C_j|\mathbf{x})$
- Class prob, more useful than knowing max class prob.

# Data Description

- $D: (\mathbf{x}_j, y_j), j = 1, \dots, N$ 
  - observation  $\mathbf{x}_j$  comes with class label  $y_j$
  - $y_j = C_j$  if  $\mathbf{x}_j \in C_j$
- Constructing  $P(C_j|\mathbf{x})$  given  $D$
- Two approaches: *generative* and *discriminative*

# Example Training Data

Three Classes: Two Features



$\mathbf{x} = [x_1, x_2]$  - features

$C_1 = \text{r}$ ,  $C_2 = \text{g}$  and  $C_3 = \text{b}$



# Nearest Centroid Classifier

- Imports:

- `from sklearn.neighbors.nearest_centroid import NearestCentroid`
- `from sklearn.metrics import confusion_matrix`

- Train:

- `clf = NearestCentroid()`
- `clf.fit(X, y)`

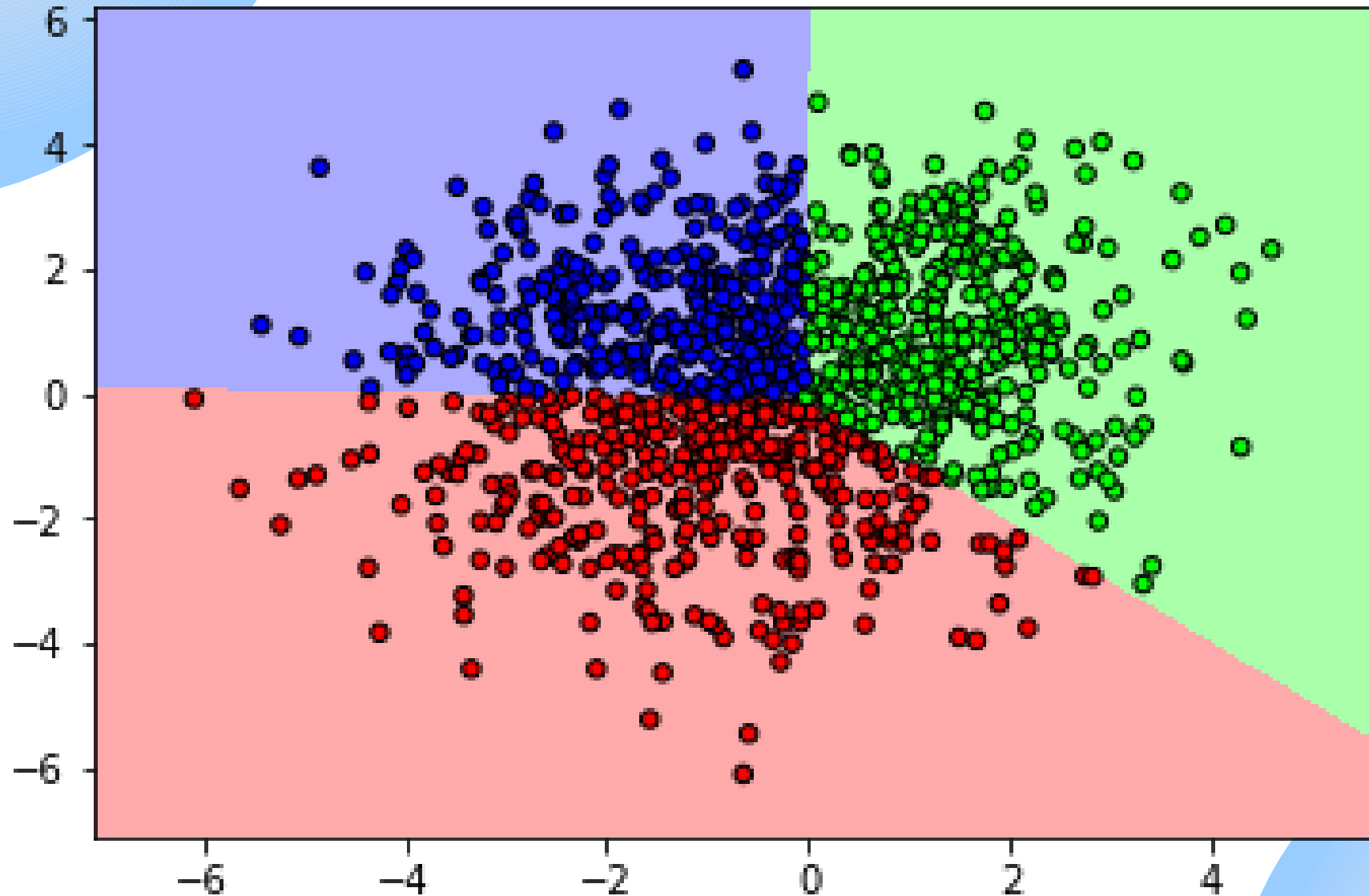
- Predict:

- `y_pred = clf.predict(X)`

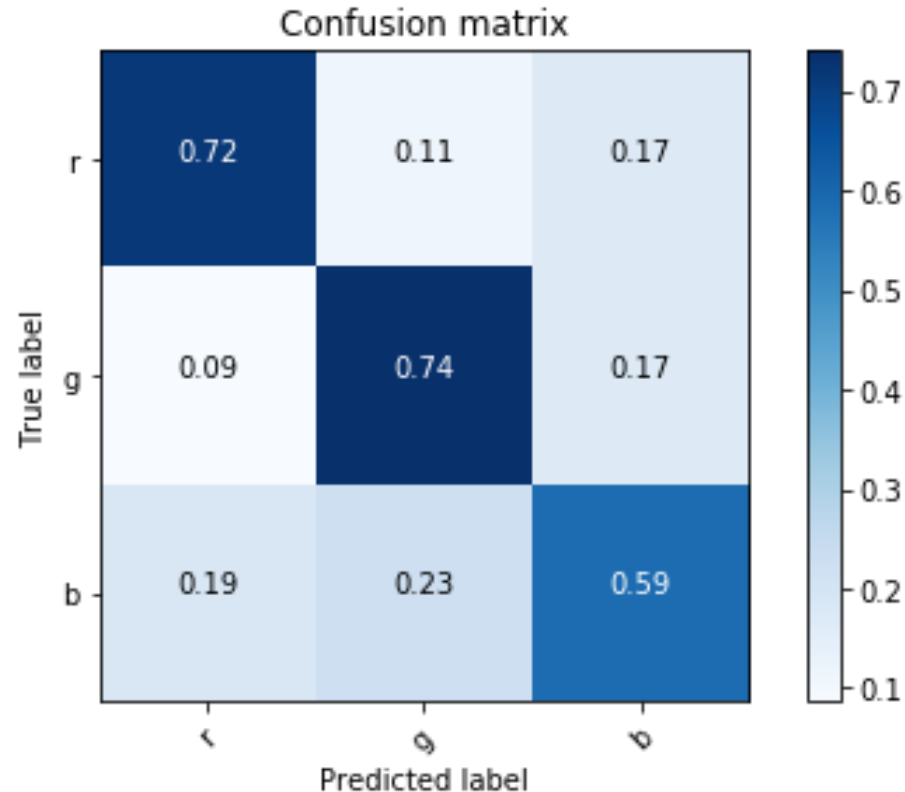
- Confusion Matrix:

- `cm = confusion_matrix(y, y_pred)`

# Decision Boundary



# Confusion Matrix



$M_{ij}$  is % of observations in class  $i$   
predicted to be in class  $j$ .

# Generative Approach

- Estimate class-conditionals:  $p(\mathbf{x}|C_j)$
- Posterior (Bayes Theorem):
  - $P(C_j|\mathbf{x}) \propto p(\mathbf{x}|C_j)P(C_j)$
  - Introduce  $P(C_j)$
- Probabilistic Generative Models (PGM)

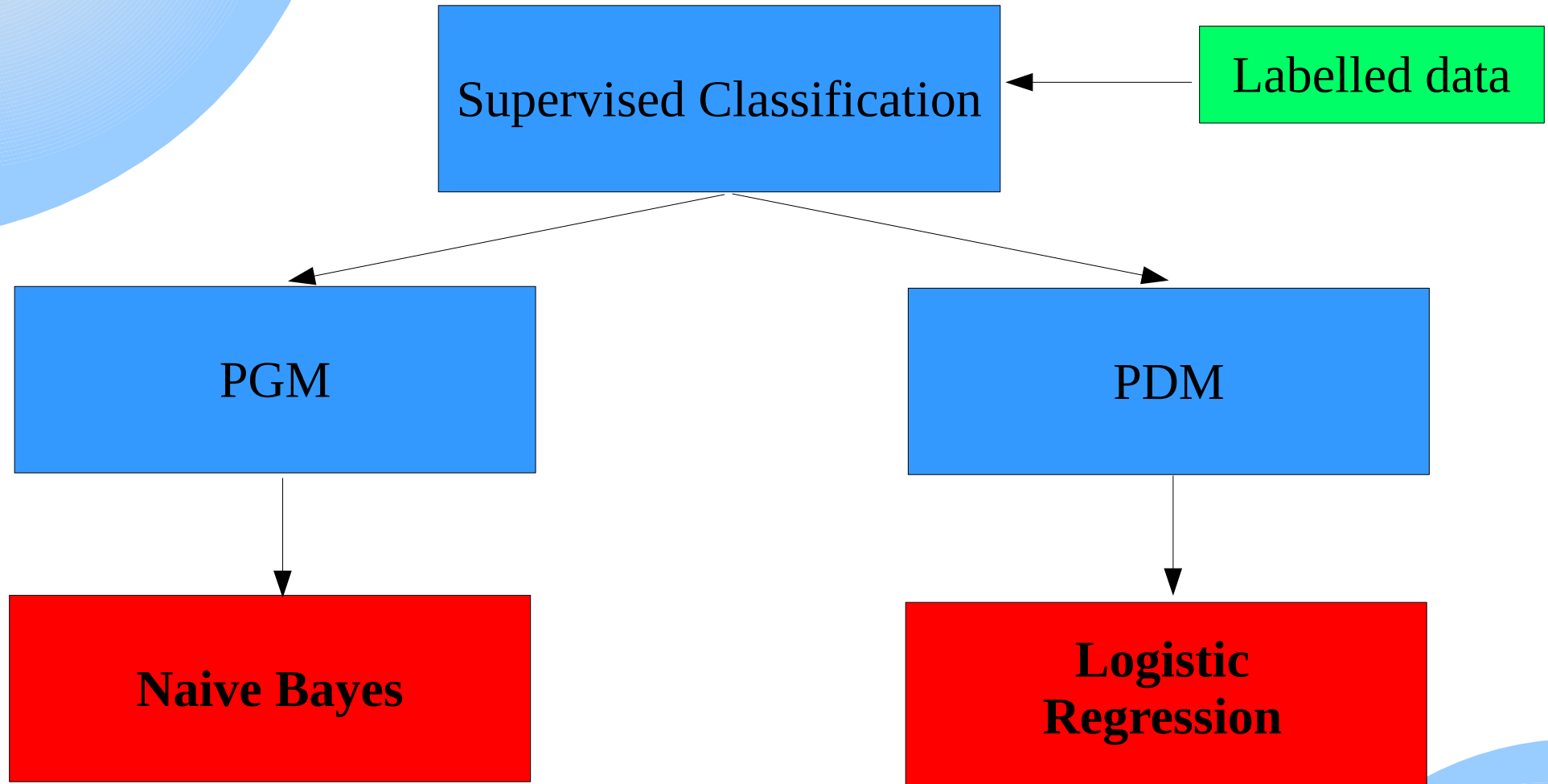
# Discriminative Approach

- Dispenses with:  $p(\mathbf{x}|C_j)$
- Directly compute posterior  $P(C_j|\mathbf{x})$
- Probabilistic Discriminative Models (PDM)

# Generative vs Discriminative

<b>Generative</b>	<b>Discriminative</b>
Wasteful	Unwasteful
Training Straightforward	Training Harder
Ignores Class Dependence	Incorporates Class Dependence
Class Data	All Data
Separate Classes	Max Class Differences

# Supervised Classification



# Naive Bayes

- Imports:

- `from sklearn.naive_bayes import GaussianNB`
- `from sklearn.metrics import confusion_matrix`

- Train:

- `clf = GaussianNB()`
- `clf.fit(X, y)`

- Predict:

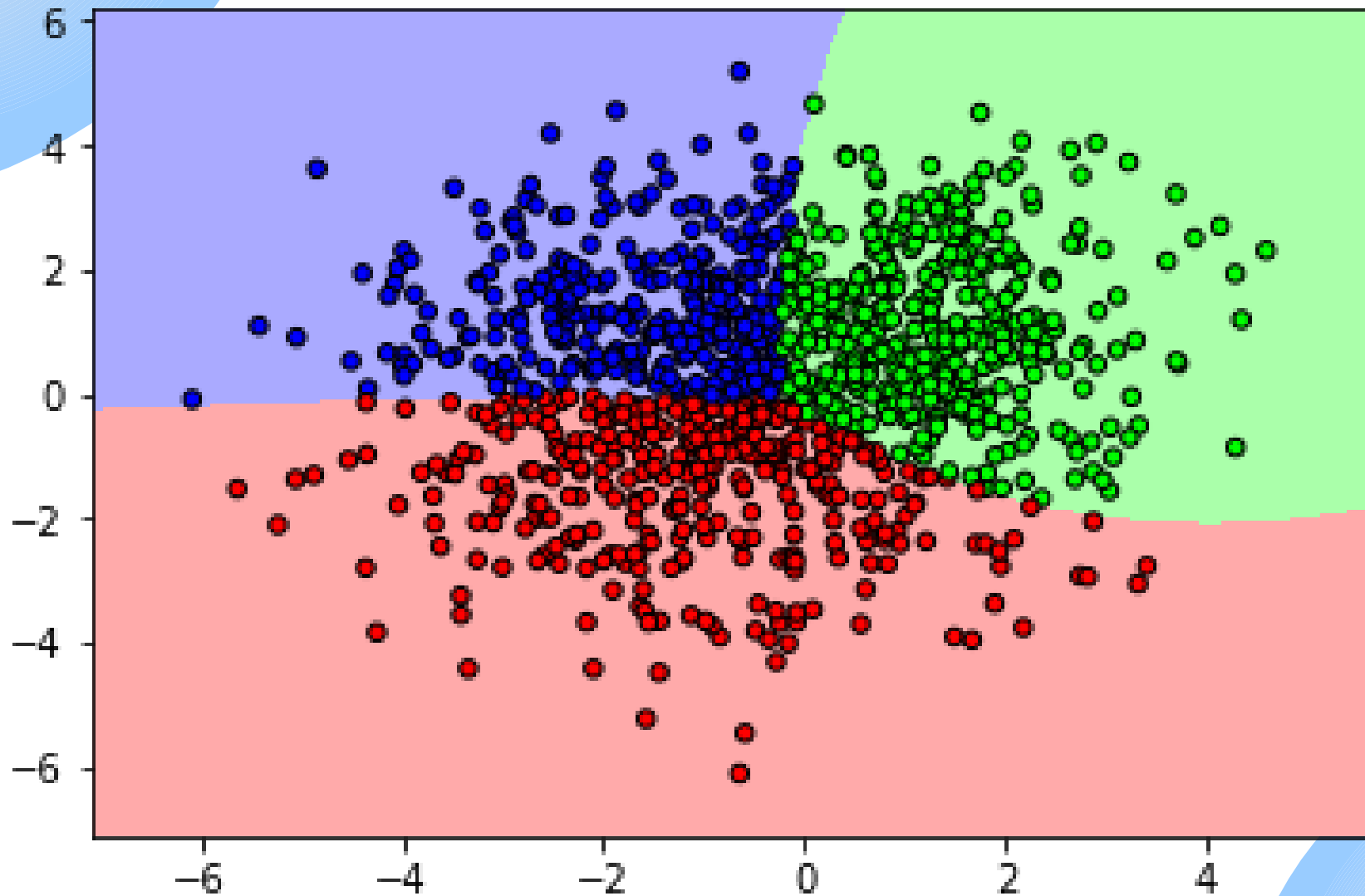
- `y_pred = clf.predict(X)`

- Confusion Matrix:

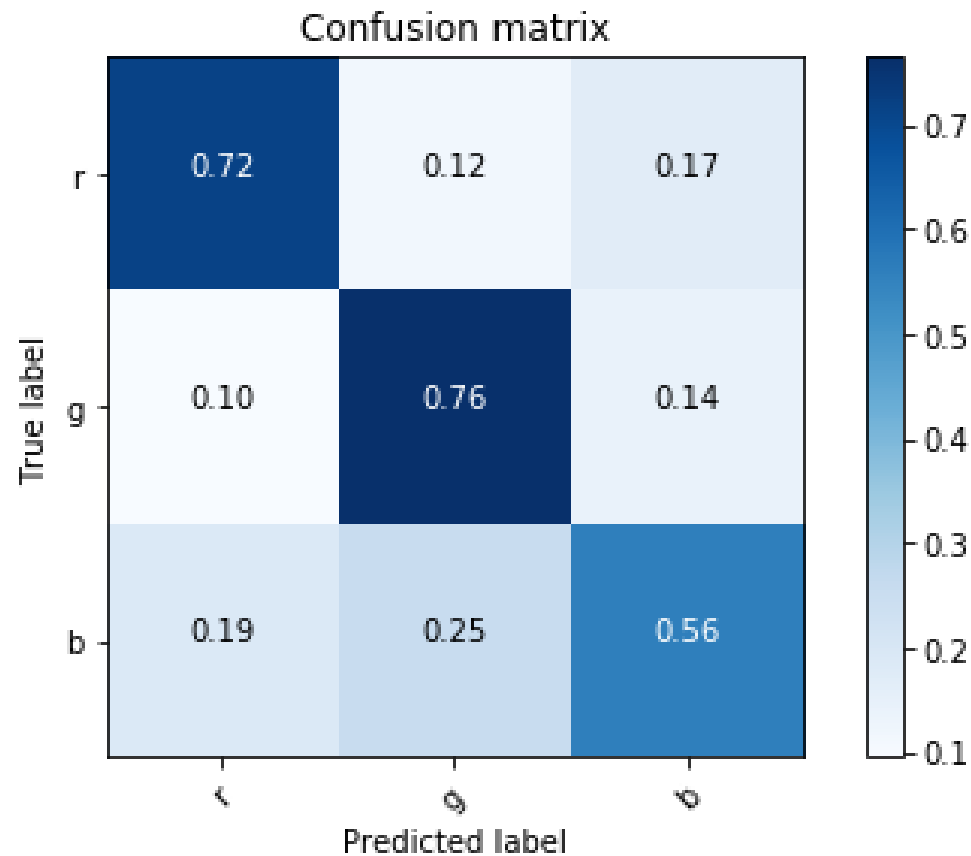
- `cm = confusion_matrix(y, y_pred)`



# Decision Boundary



# Confusion Matrix



# Logistic Regression

- Imports:

- `from sklearn.linear_model import LogisticRegression as logis`
- `from sklearn.metrics import confusion_matrix`

- Train:

- `clf = linear_model.LogisticRegression(C=1e5)`
- `clf.fit(X, y)`

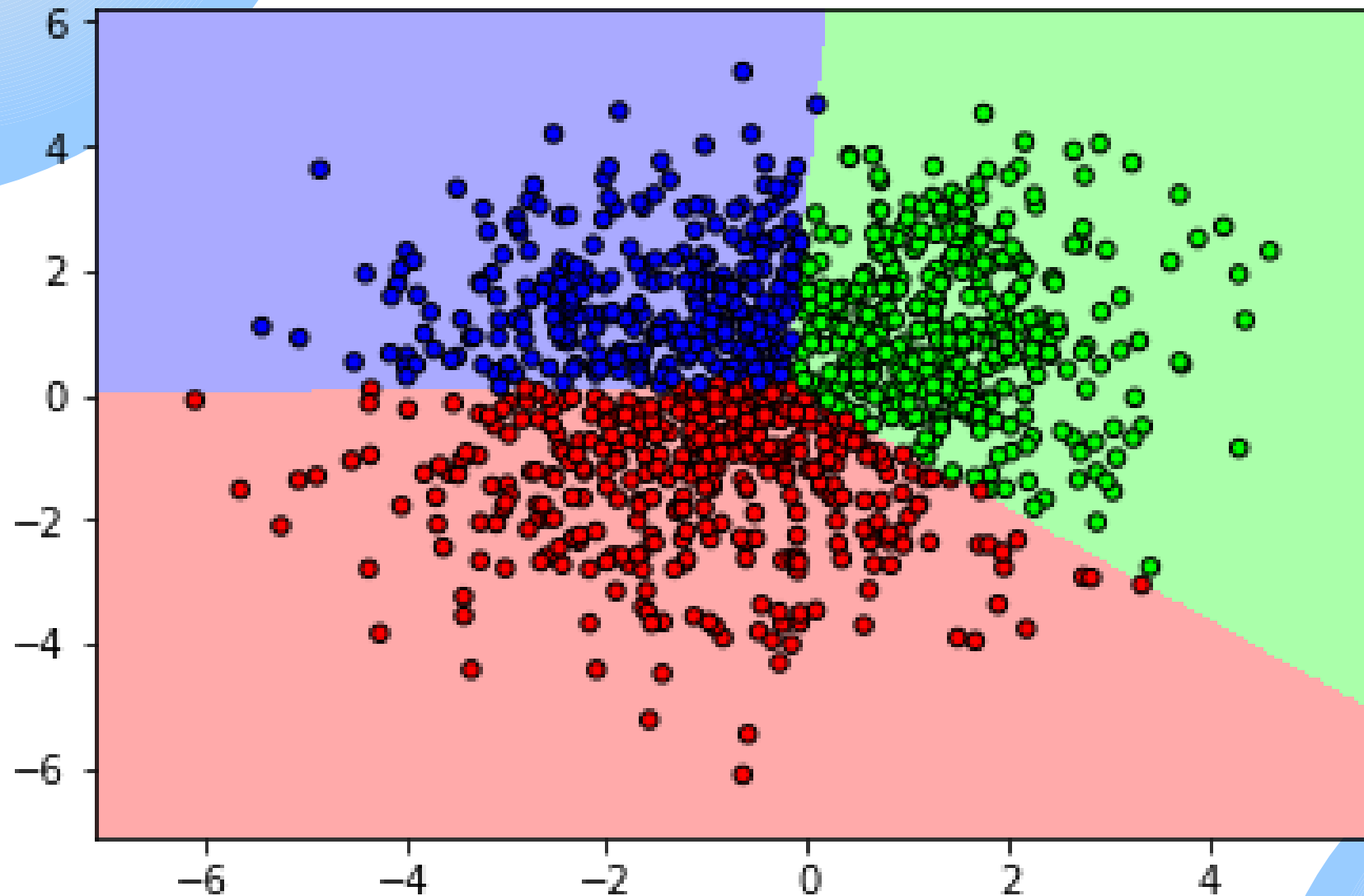
- Predict:

- `y_pred = clf.predict(X)`

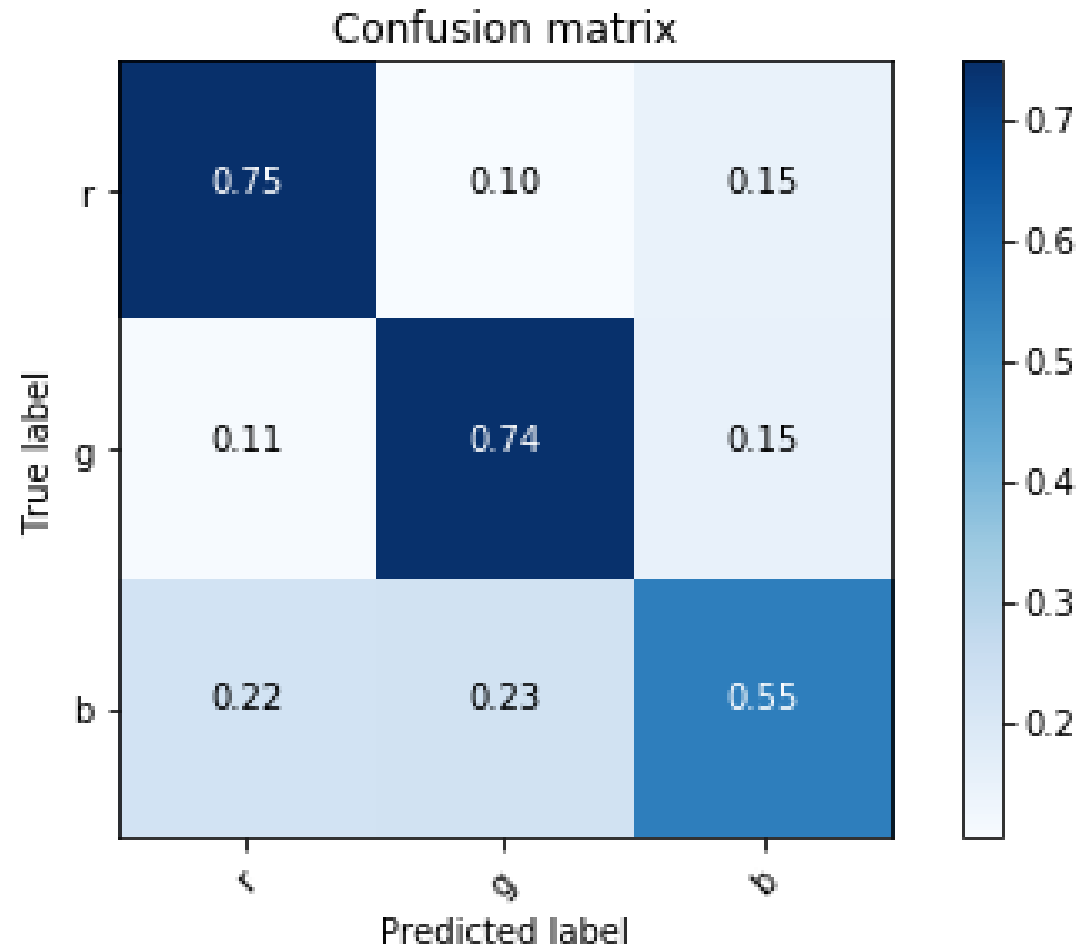
- Confusion Matrix:

- `cm = confusion_matrix(y, y_pred)`

# Decision Boundary

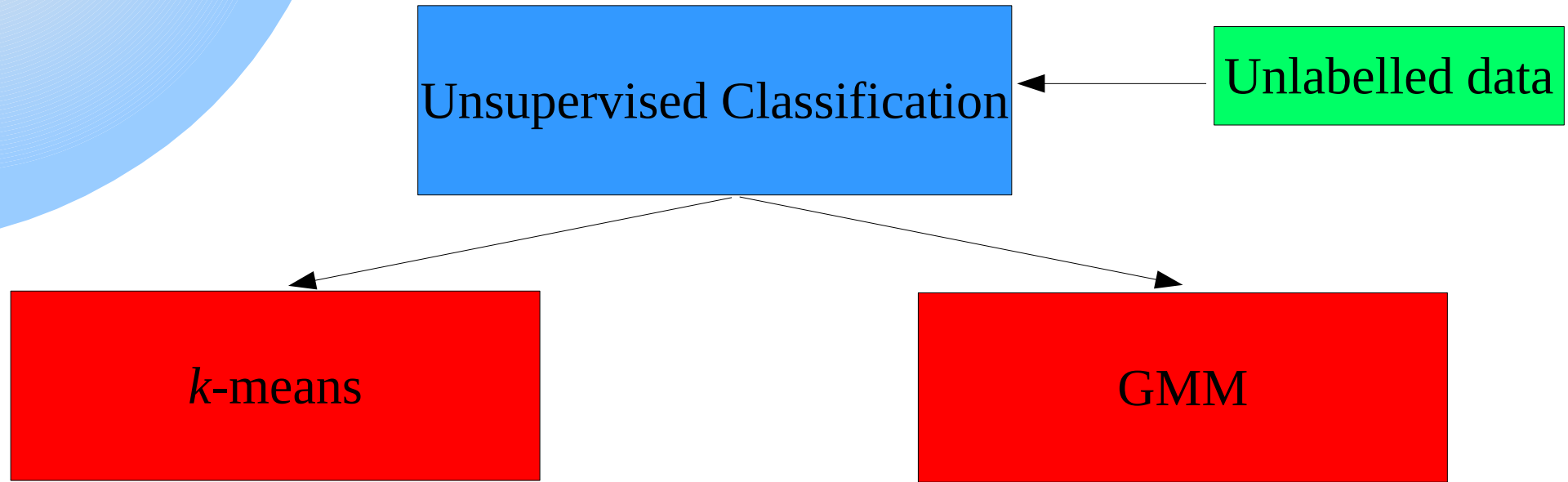


# Confusion Matrix



# Unsupervised Classification (Chap 5)

# Unsupervised Classification



- Clustering data into *k-clusters* without any class labels. Unlabelled data.

# *k*-means

- Imports:

- `from sklearn.cluster import KMeans`
- `from sklearn.metrics import confusion_matrix`

- Train:

- `kmeans = KMean(n_clusters=3)`
- `kmeans.fit(X)` ← **No-labels**

- Predict:

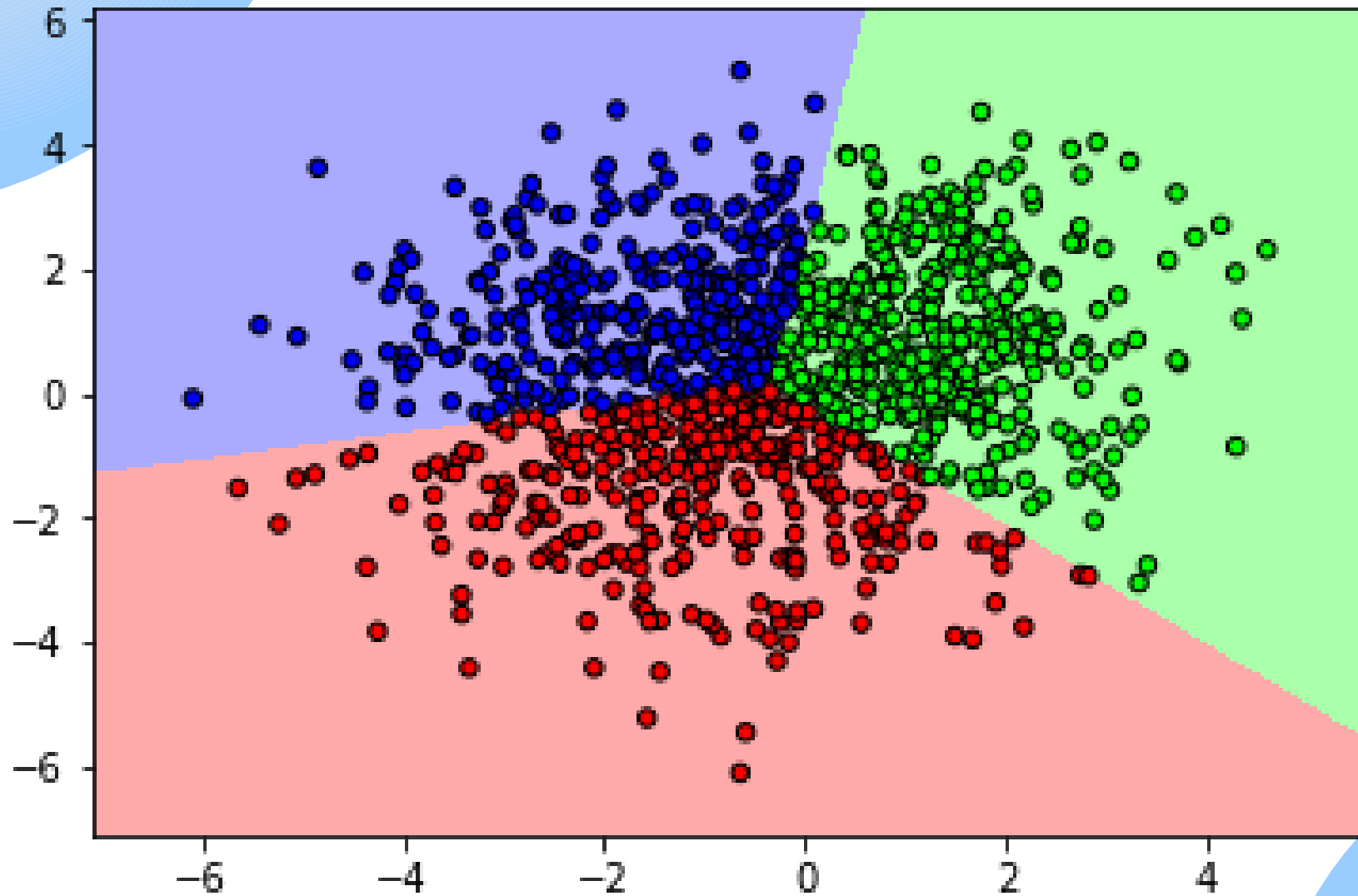
- `y_pred = kmeans.predict(X)` ← **Labels may need to be flipped**

- Confusion Matrix:

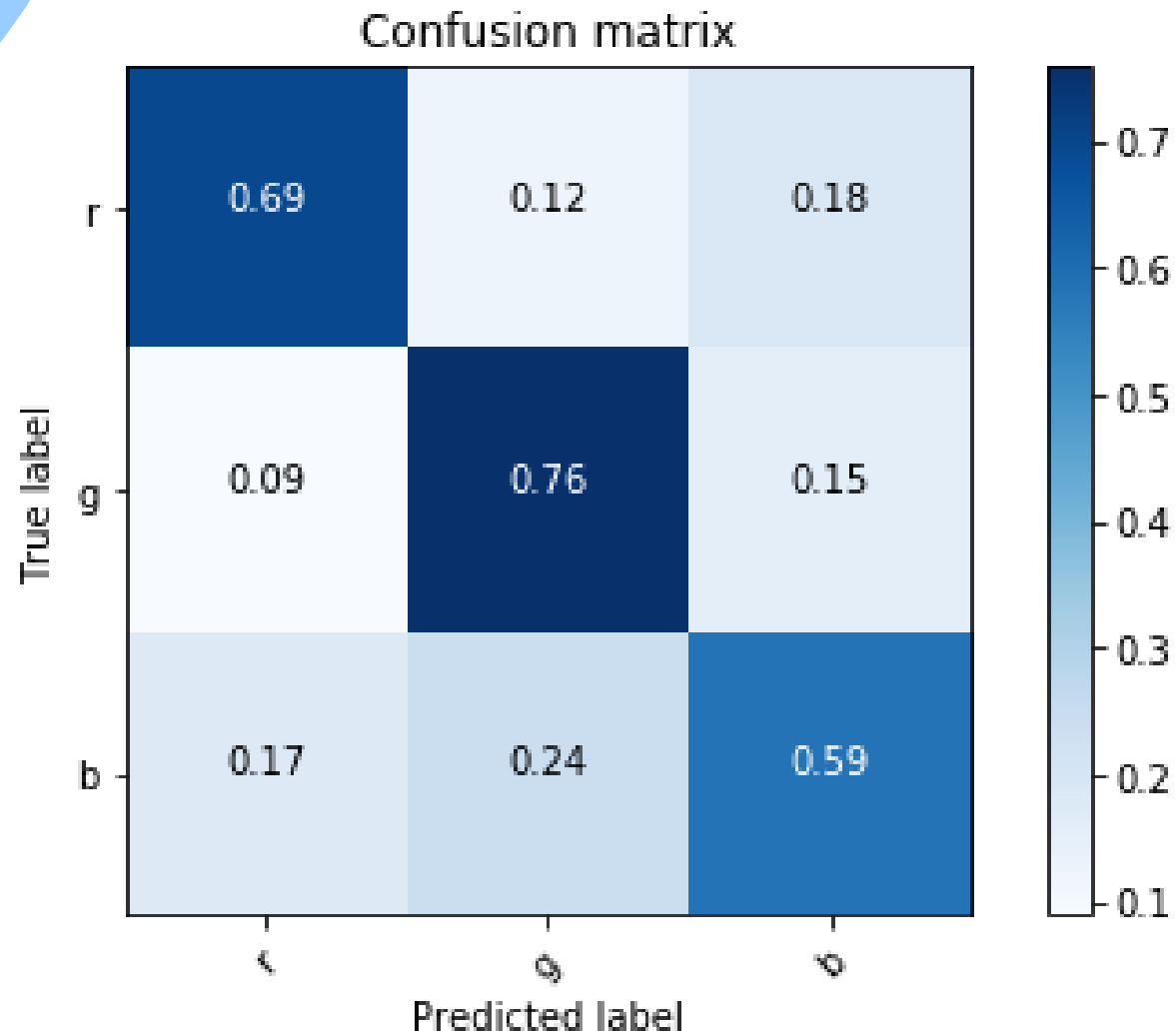
- `cm = confusion_matrix(y, y_pred)`



# Decision Boundary



# Confusion Matrix



# Gaussian Mixture Model

- Imports:

- `from sklearn.mixture import GaussianMixture`
  - `from sklearn.metrics import confusion_matrix`

- Train:

- `gmm = mixture.GaussianMixture(n_components=3)`
  - `gmm.fit(X)` ← **No-labels**

- Predict:

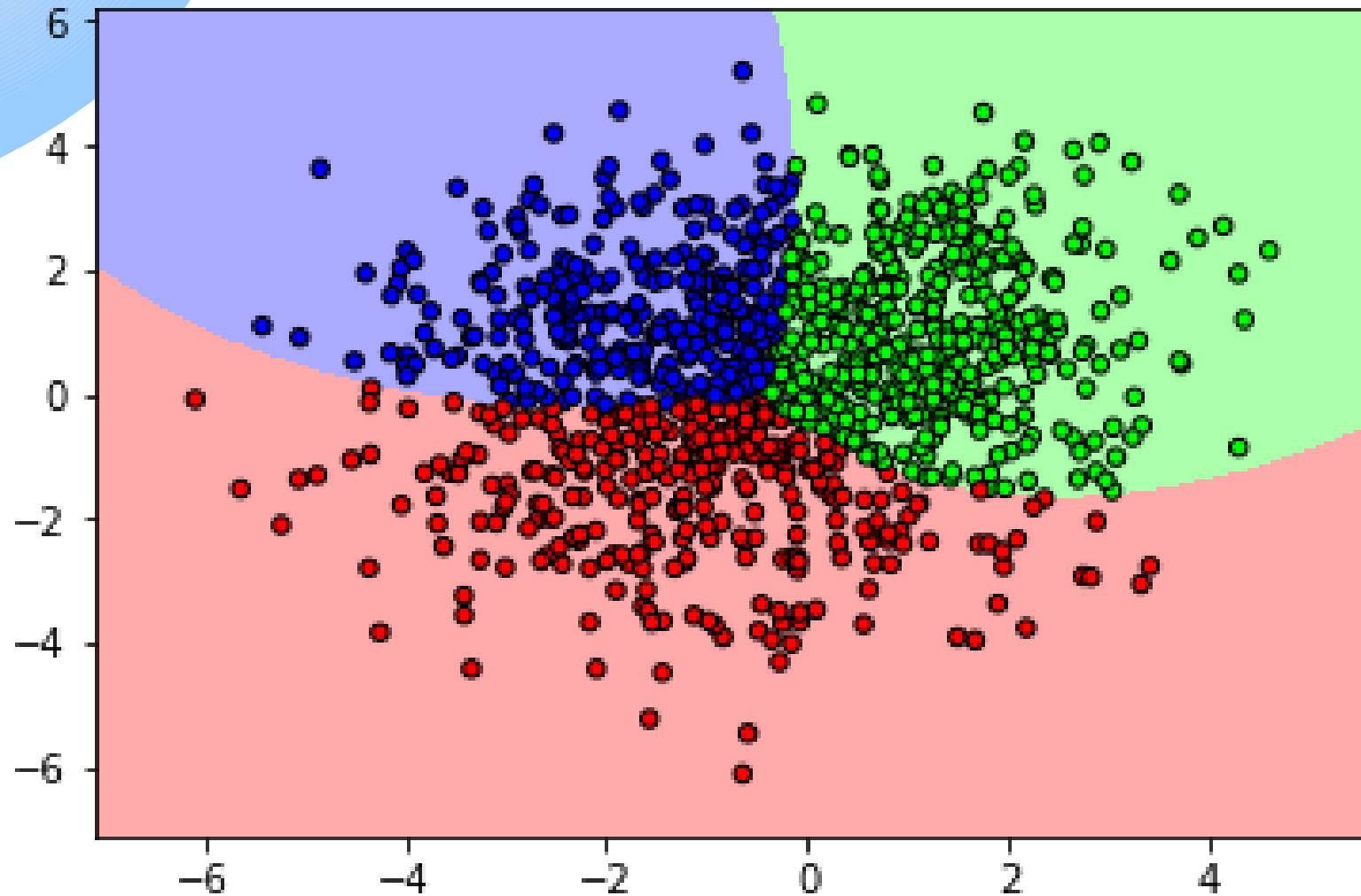
- `y_pred = gmm.predict(X)`

**Labels may need  
to be flipped**

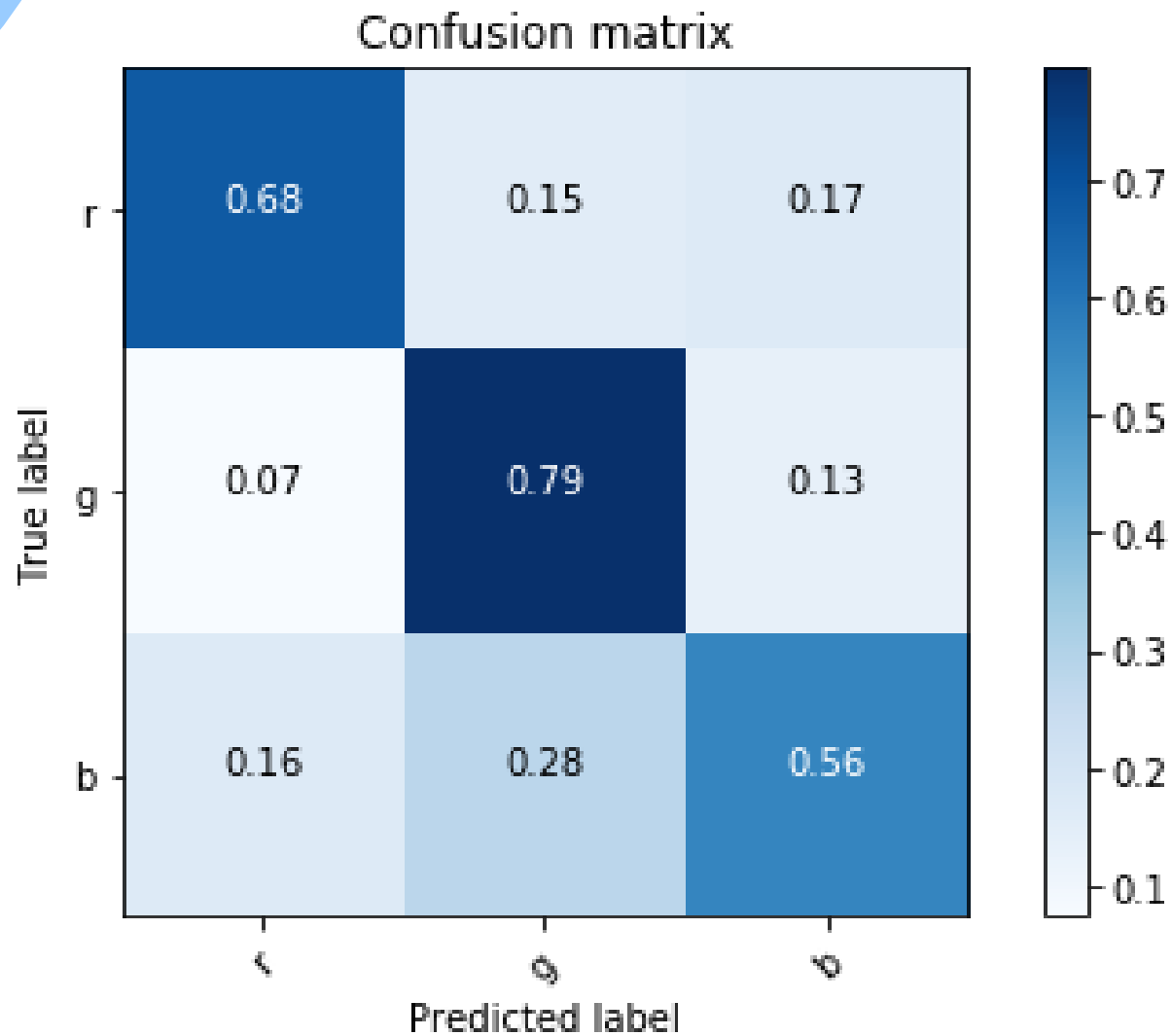
- Confusion Matrix:

- `cm = confusion_matrix(y, y_pred)`

# Decision Boundary



# Confusion Matrix



# Conclusion

- Introduction to supervised classification (labelled data):
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  - Discriminative: Logistic Regression
- Introduction to unsupervised classification:
  - $k$ -means
  - GMM