Day 09 - Logistic Regression

Oct. 6, 2020

CMSE

Administrative

- **Homework 3** will be assigned Friday 10/9 and due Friday 10/23
- **Midterm** will be given Thursday 10/29 in class

From Pre-Class Assignment

Useful Stuff

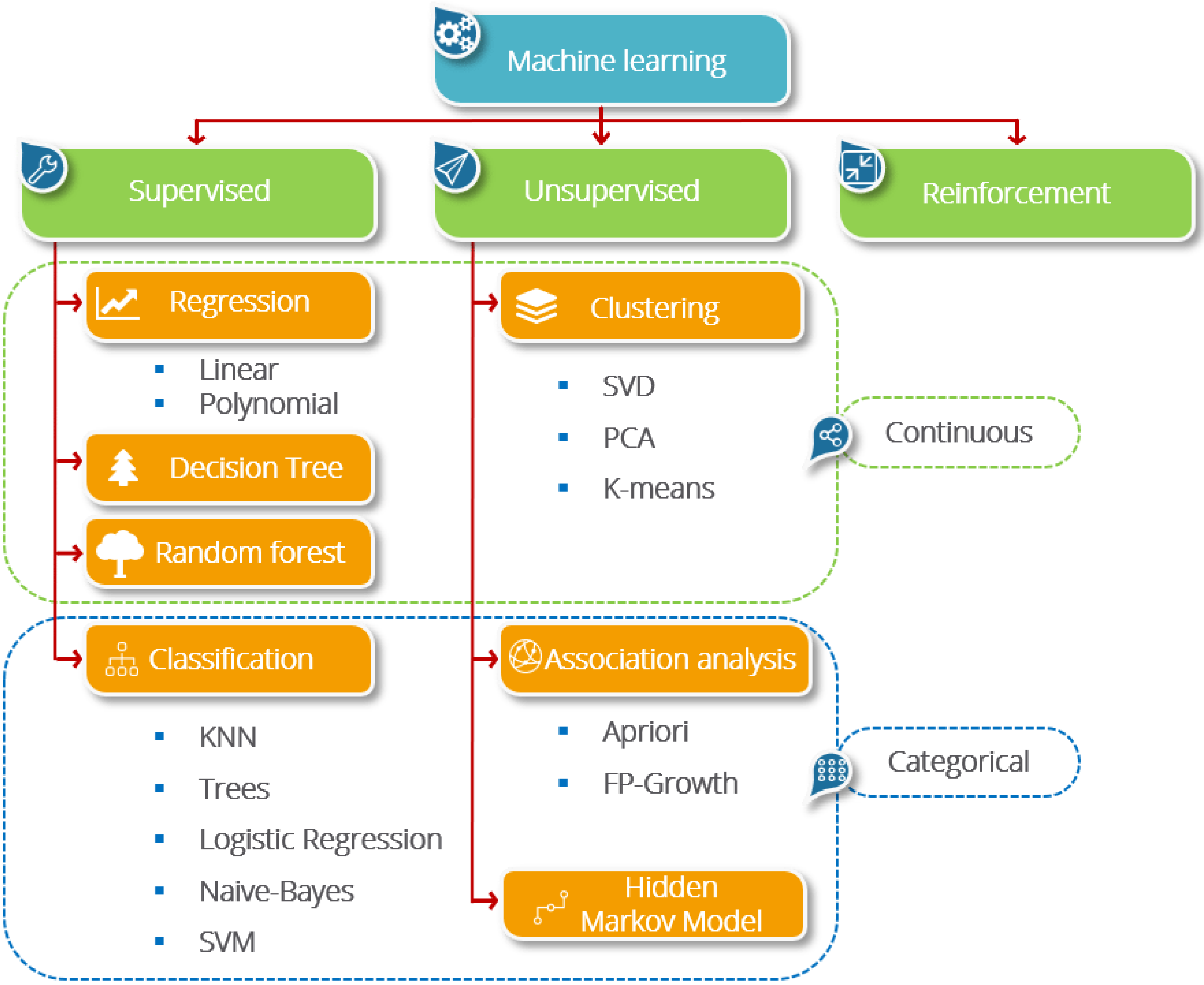
- Videos from Google were helpful to understand the scope of Machine Learning
- I have a better understanding of train/test split

Challenging bits

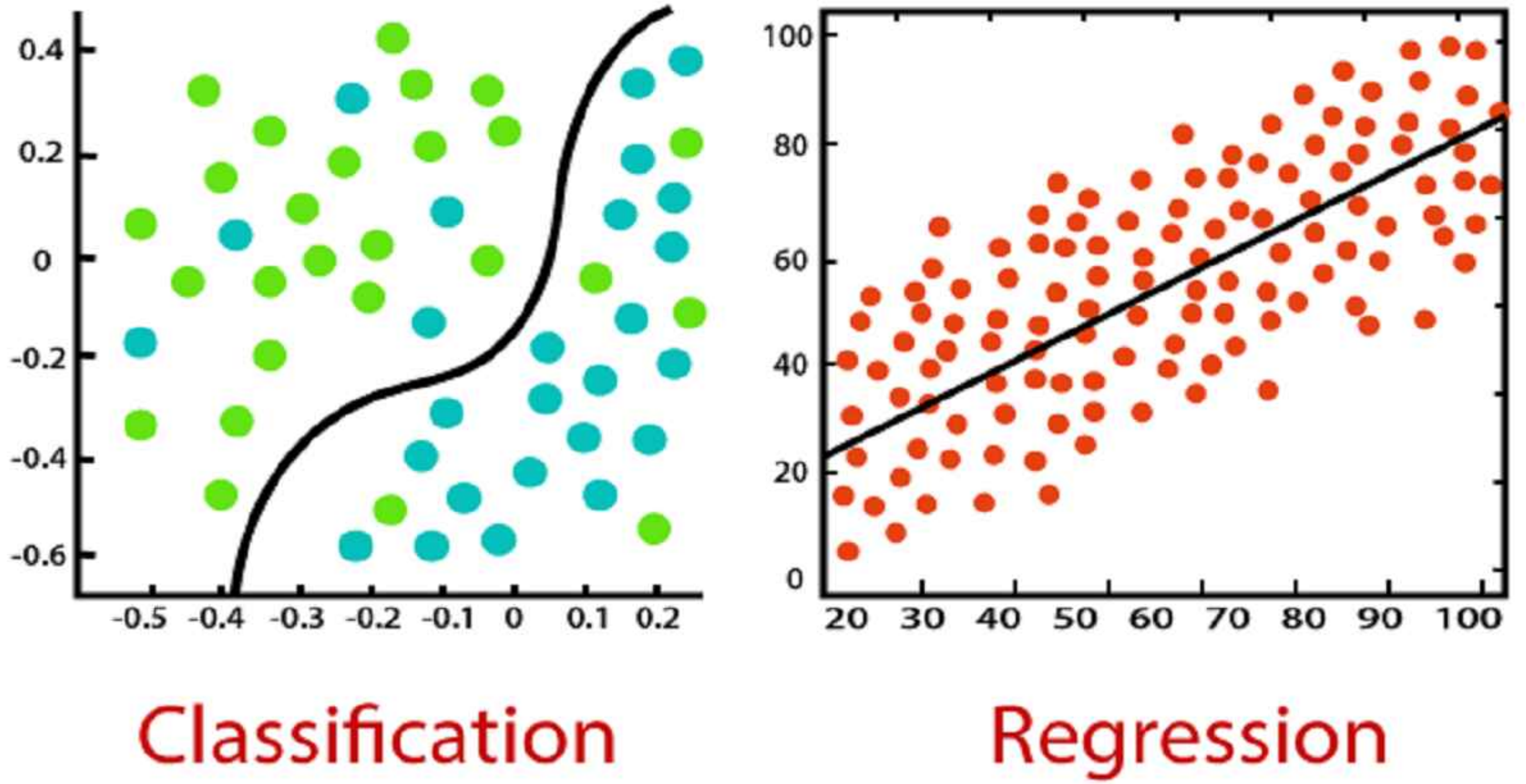
- I am still a little confused about why we split the data
- I am not sure what `make_classification` is doing
- What are redundant and informative features? How do we see them in the plots?

We will be doing classification tasks for a few weeks, so we will get lots of practice

Machine Learning


Machine learning
Supervised
Unsupervised
Reinforcement
Regression
Linear
Polynomial
Decision Tree
Random forest
Clustering
SVD
PCA
K-means
Continuous
Classification
KNN
Trees
Logistic Regression
Naive-Bayes
SVM
Association analysis
Apriori
FP-Growth
Hidden Markov Model
Categorical

Classification



Classification Algorithms

- **Logisitic Regression:** The most traditional technique; was developed and used prior to ML; fits data to a "sigmoidal" (s-shaped) curve; fit coefficients are interpretable
- **K Nearest Neighbors (KNN):** A more intuitive method; nearby points are part of the same class; fits can have complex shapes
- **Support Vector Machines (SVM):** Developed for linear separation (i.e., find the optimal "line" to separate classes; can be extended to curved lines through different "kernels"
- **Decision Trees:** Uses binary (yes/no) questions about the features to fit classes; can be used with numerical and categorical input
- **Random Forest:** A collection of randomized decision trees; less prone to overfitting than decision trees; can rank importance of features for prediction
- **Gradient Boosted Trees:** An even more robust tree-based algorithm

We will learn Logisitic Regression, KNN, and SVM, but `sklearn` provides access to the other three methods as well.

Generate some data

`make_classification` lets us make fake data and control the kind of data we get.

- `n_features` - the total number of features that can be used in the model
- `n_informative` - the total number of features that provide unique information for classes
    - say 2, so x_0 and x_1
- `n_redundant` - the total number of features that are built from informative features (i.e., have redundant information)
    - say 1, so $x_2 = c_0 x_0 + c_1 x_1$
- `n_class` - the number of class labels (default 2: 0/1)
- `n_clusters_per_class` - the number of clusters per class

In [63]:

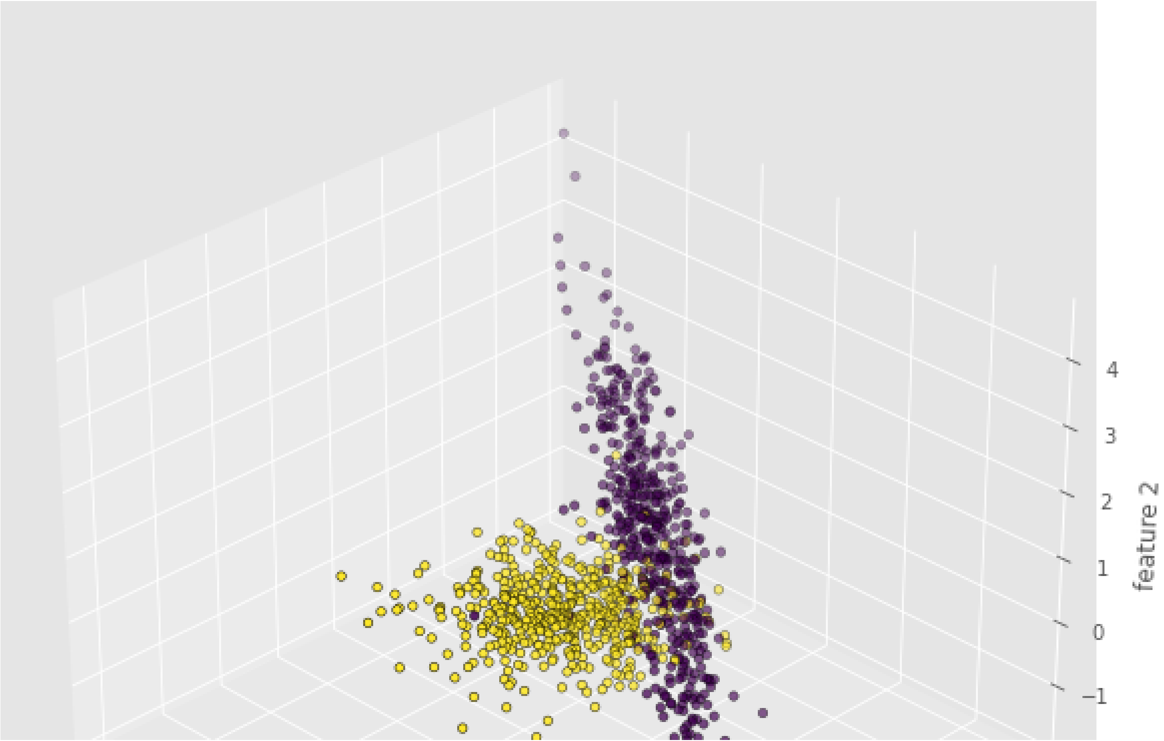
```
import matplotlib.pyplot as plt
plt.style.use('seaborn-colorblind')
from sklearn.datasets import make_classification

features, class_labels = make_classification(n_samples = 1000,
                                              n_features = 3,
                                              n_informative = 2,
                                              n_redundant = 1,
                                              n_clusters_per_class=1,
                                              random_state=201)
```

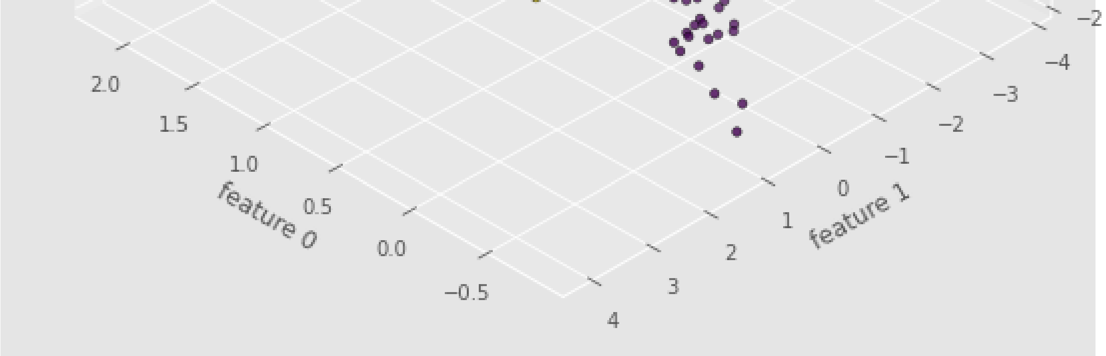
In [64]:

```python
## Let's look at these 3D data
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure(figsize=(8,8))
ax = Axes3D(fig, rect=[0, 0, .95, 1], elev=30, azim=135)

xs = features[:, 0]
ys = features[:, 1]
zs = features[:, 2]

ax.scatter3D(xs, ys, zs, c=class_labels, ec='k')
ax.set_xlabel('feature 0')
ax.set_ylabel('feature 1')
ax.set_zlabel('feature 2')
```

Out[64]:

```
Text(0.5, 0, 'feature 2')
```

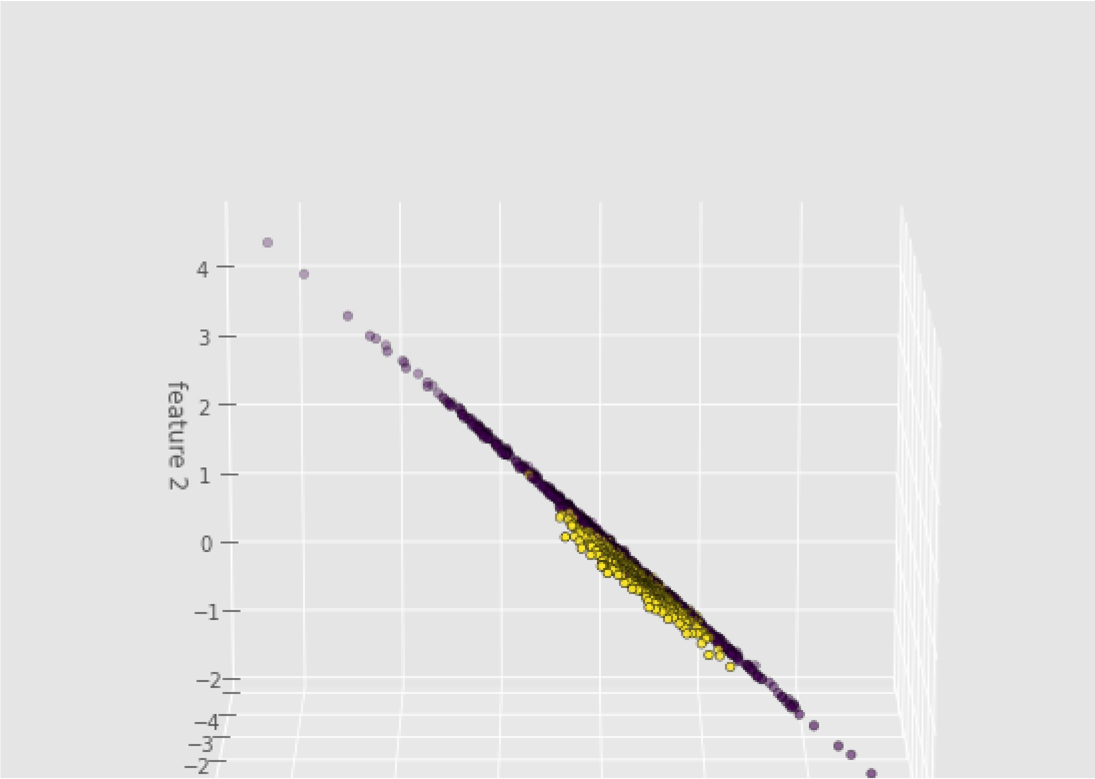


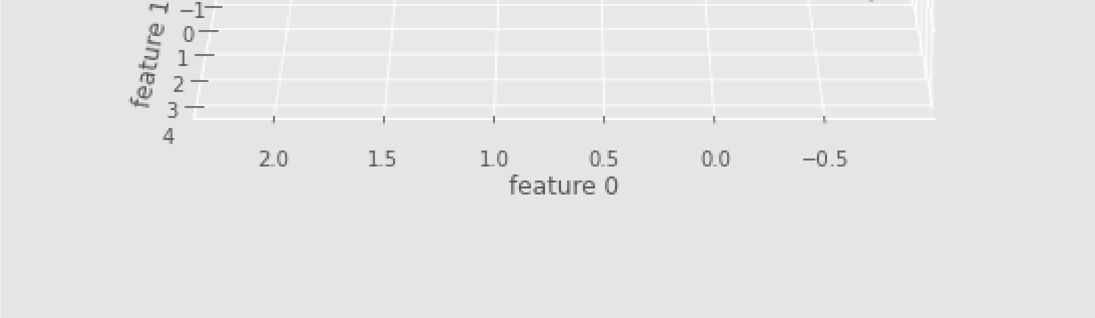


feature 0
feature 1
2.0
1.5
1.0
0.5
0.0
−0.5
4
3
2
1
0
−1
−2
−3
−4
−2

In [65]:
```python
## From a different angle, we see the 2D nature of the data
fig = plt.figure(figsize=(8,8))
ax = Axes3D(fig, rect=[0, 0, .95, 1], elev=15, azim=90)

xs = features[:, 0]
ys = features[:, 1]
zs = features[:, 2]

ax.scatter3D(xs, ys, zs, c=class_labels, ec = 'k')
ax.set_xlabel('feature 0')
ax.set_ylabel('feature 1')
ax.set_zlabel('feature 2')
```

Out[65]:
```
Text(0.5, 0, 'feature 2')
```



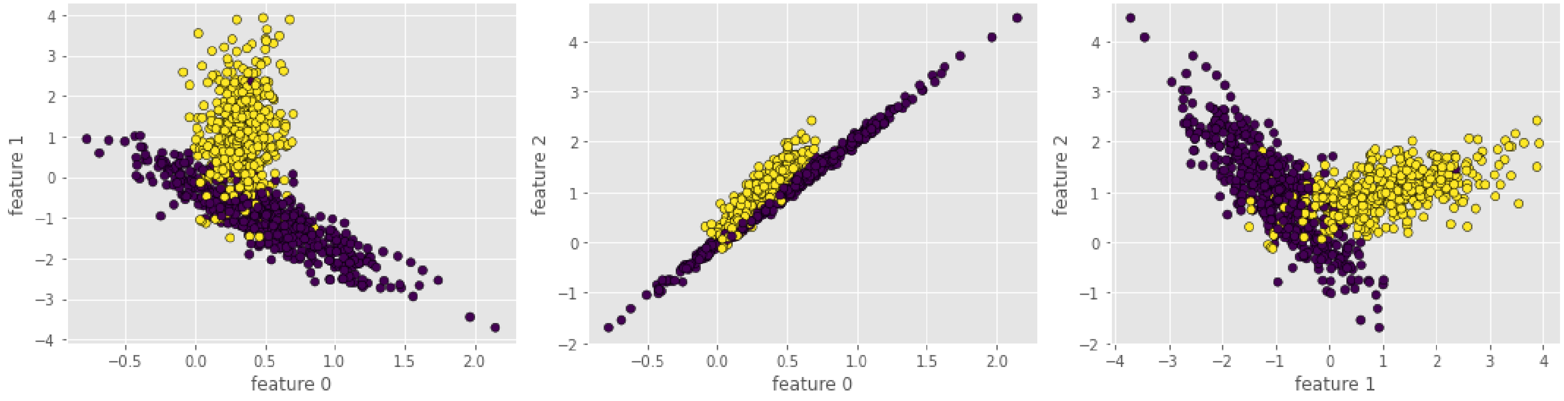

−1
0
1
2
3
4
feature 1
2.0
1.5
1.0
0.5
0.0
−0.5
feature 0

Feature Subspaces

For higher dimensions, we have take 2D slices of the data (called "projections" or "subspaces")

In [66]:

```
f, axs = plt.subplots(1,3,figsize=(15,4))
plt.subplot(131)
plt.scatter(features[:, 0], features[:, 1], marker = 'o', c = class_labels, ec =
'k')
plt.xlabel('feature 0')
plt.ylabel('feature 1')

plt.subplot(132)
plt.scatter(features[:, 0], features[:, 2], marker = 'o', c = class_labels, ec =
'k')
plt.xlabel('feature 0')
plt.ylabel('feature 2')

plt.subplot(133)
plt.scatter(features[:, 1], features[:, 2], marker = 'o', c = class_labels, ec =
'k')
plt.xlabel('feature 1')
plt.ylabel('feature 2')

plt.tight_layout()
```

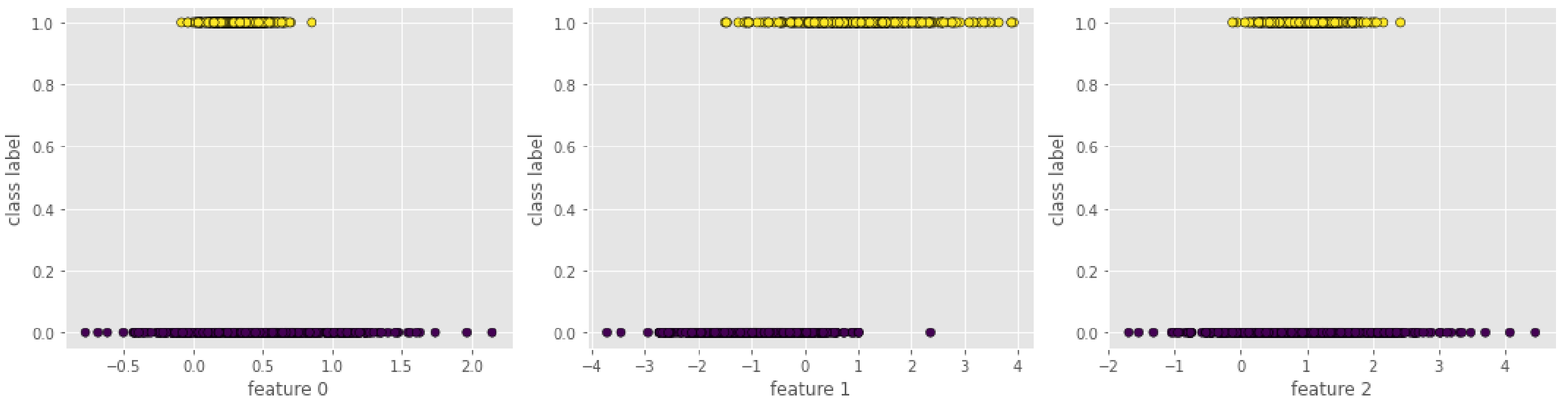


What about Logistic Regression?

Logistic Regression attempts to fit a sigmoid (S-shaped) function to your data. This shapes assumes that the probability of finding class 0 versus class 1 increases as the feature changes value.

In [70]:

```
f, axs = plt.subplots(1,3,figsize=(15,4))
plt.subplot(131)
plt.scatter(features[:,0], class_labels, c=class_labels, ec='k')
plt.xlabel('feature 0')
plt.ylabel('class label')

plt.subplot(132)
plt.scatter(features[:,1], class_labels, c=class_labels, ec='k')
plt.xlabel('feature 1')
plt.ylabel('class label')

plt.subplot(133)
plt.scatter(features[:,2], class_labels, c=class_labels, ec='k')
plt.xlabel('feature 2')
plt.ylabel('class label')

plt.tight_layout()
```



Questions, Comments, Concerns?