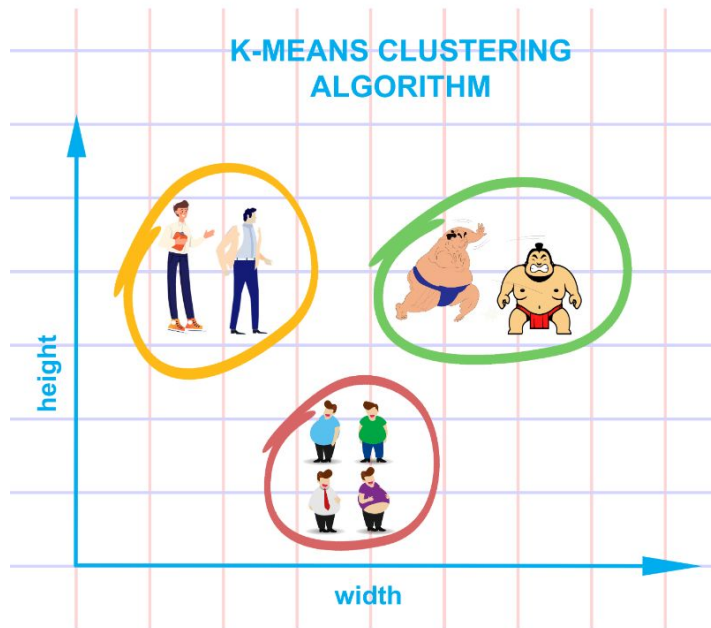


UNSUPERVISED LEARNING

Clustering Algorithms

K-Means Clustering

```
from sklearn.cluster import  
KMeans  
  
data = list(zip(x, y))  
inertias = []  
  
for i in range(1,11):  
    kmeans =  
    KMeans(n_clusters=i)  
    kmeans.fit(data)  
  
    inertias.append(kmeans.inertia_)  
  
plt.plot(range(1,11), inertias,  
marker='o')  
plt.title('Elbow method')  
plt.xlabel('Number of clusters')  
plt.ylabel('Inertia')  
plt.show()
```



Hierarchical Clustering

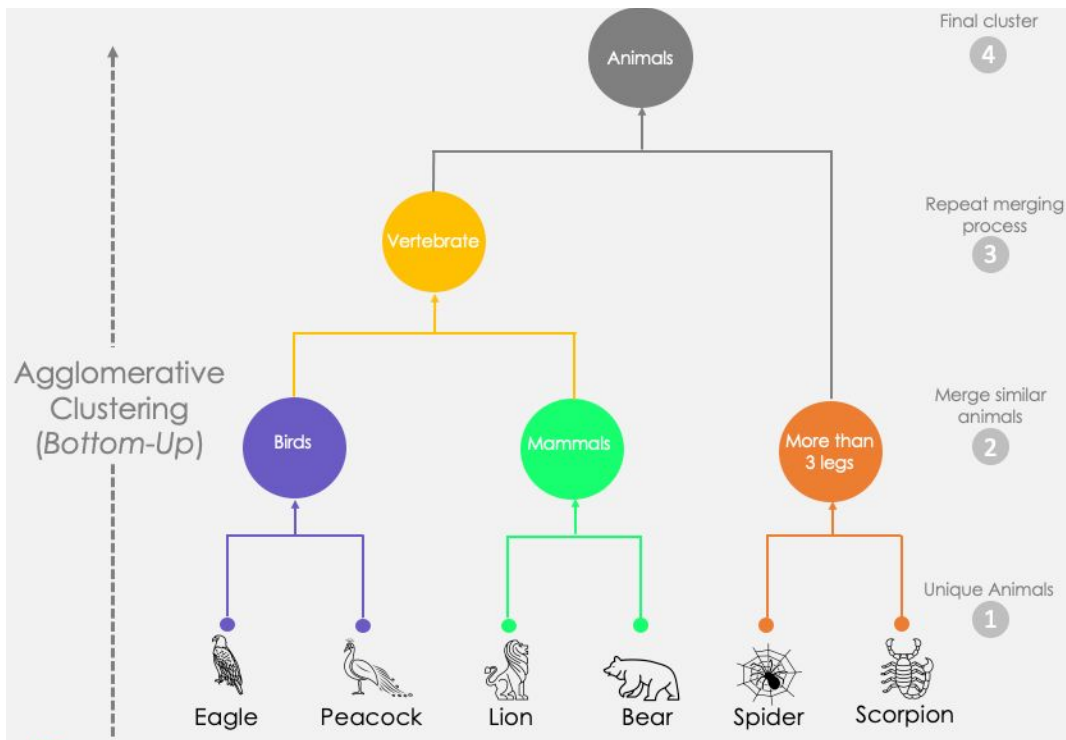
```
import numpy as np
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy
import dendrogram, linkage
```

```
x = [4, 5, 10, 4, 3, 11, 14, 6,
     10, 12]
y = [21, 19, 24, 17, 16, 25, 24,
     22, 21, 21]
```

```
data = list(zip(x, y))
```

```
linkage_data = linkage(data,
method='ward',
metric='euclidean')
dendrogram(linkage_data)
```

```
plt.show()
```



DBSCAN

```
import numpy as np
```

```
from sklearn import metrics
```

```
from sklearn.cluster import DBSCAN
```

```
db = DBSCAN(eps=0.3, min_samples=10).fit(X)
```

```
labels = db.labels_
```

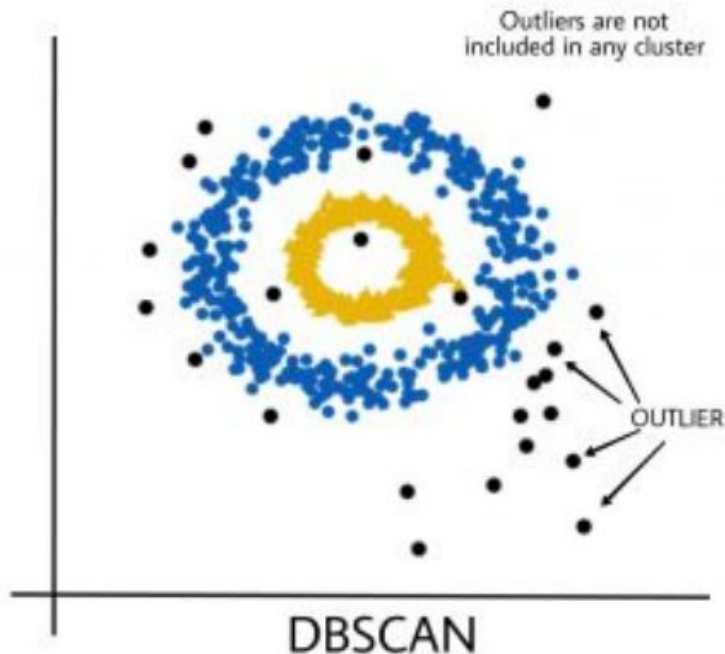
```
# Number of clusters in labels, ignoring noise if present.
```

```
n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
```

```
n_noise_ = list(labels).count(-1)
```

```
print("Estimated number of clusters: %d" % n_clusters_)
```

```
print("Estimated number of noise points: %d" % n_noise_)
```



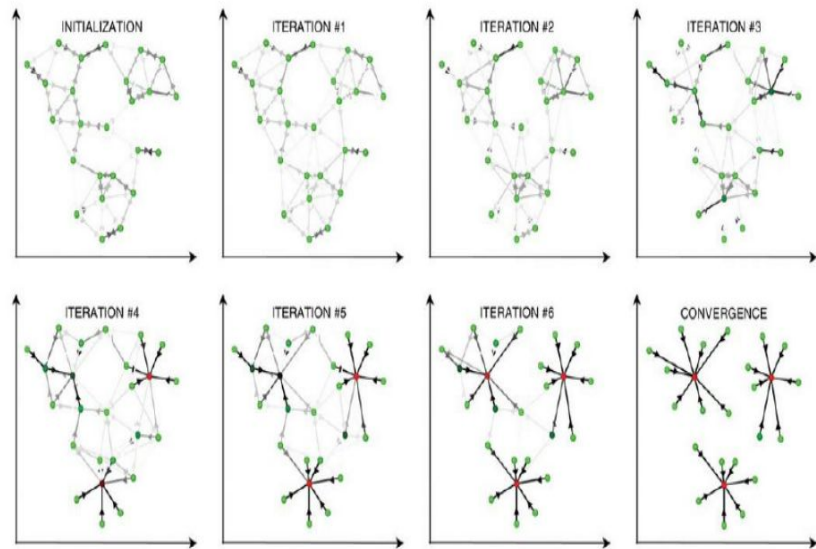
Affinity Propagation

```
from sklearn.cluster import AffinityPropagation
from sklearn import metrics
from sklearn.datasets.samples_generator import
make_blobs
```

```
centers = [[1, 1], [-1, -1], [1, -1], [-1, -1]]
X, labels_true = make_blobs(n_samples = 400, centers
= centers, cluster_std = 0.5, random_state = 0)
```

```
af = AffinityPropagation(preference = -50).fit(X)
cluster_centers_indices = af.cluster_centers_indices_
labels = af.labels_
```

```
n_clusters_ = len(cluster_centers_indices)
```

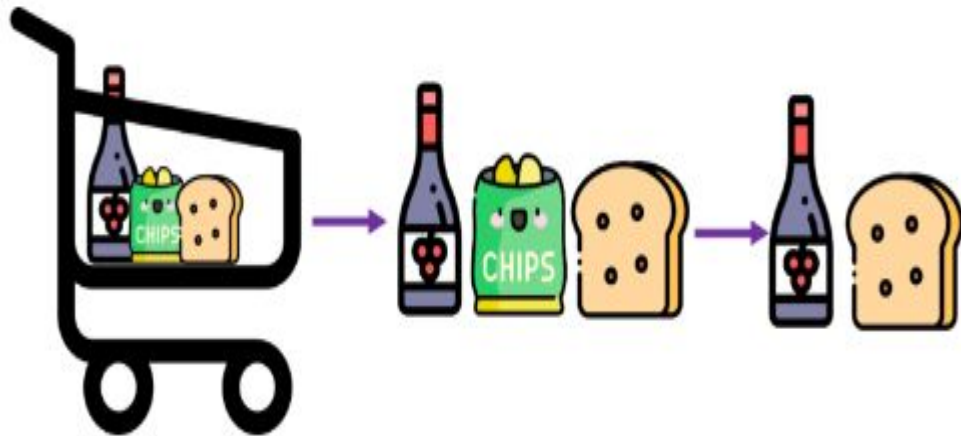


Associative Algorithms

A dark blue diagonal gradient bar that starts from the bottom left and extends towards the top right, covering the lower half of the slide.

Apriori Algorithm

1. `# Build the model`
2. `freq_items1 = AP(basket1_France,
min_support = 0.05, use_colnames = True)`
- 3.
4. `# Collect the inferred rules in a dataframe`
5. `rules1 = AR(freq_items1, metric = "lift",
min_threshold = 1)`
6. `rules1 = rules1.sort_values(['confidence',
'lift'], ascending = [False, False])`
7. `print(rules1.head())`



Eclat Algorithm

```
from pyECLAT import ECLAT
```

```
# create an instance of eclat
```

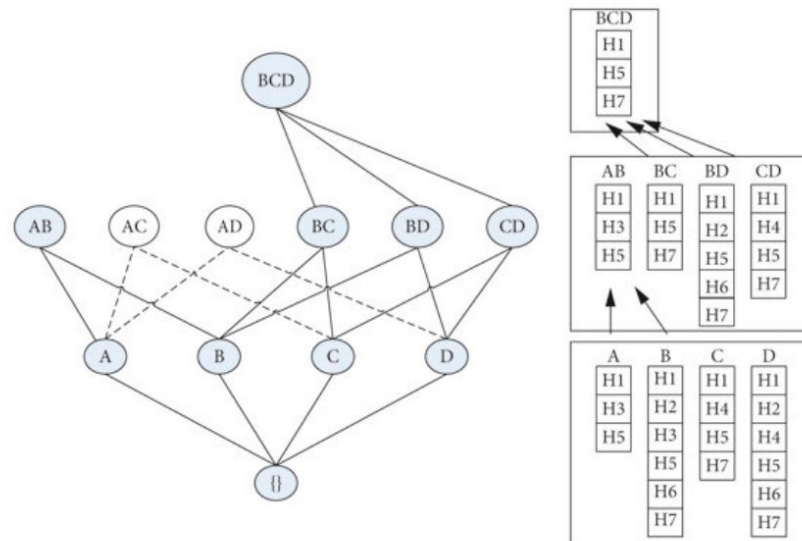
```
my_eclat = ECLAT(data=data, verbose=True)
```

```
# fit the algorithm
```

```
rule_indices, rule_supports =  
my_eclat.fit(min_support=min_support,
```

```
min_combination=min_n_products,
```

```
max_combination=max_length)
```



FP Growth

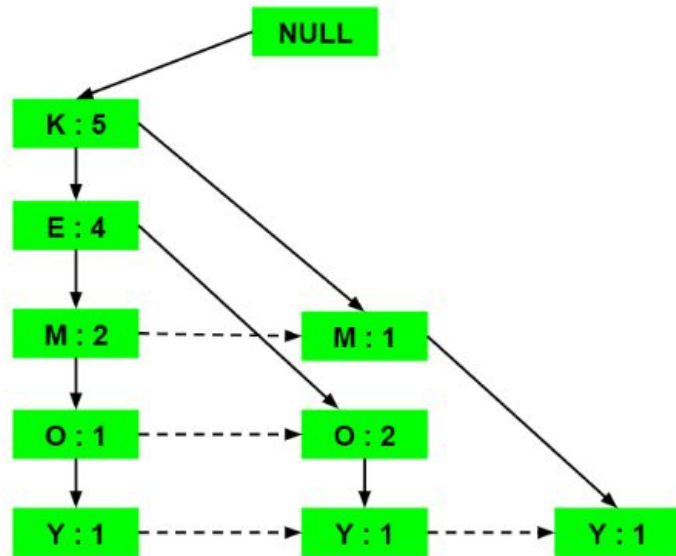
```
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import fpgrowth
```

```
# Sample transaction dataset
dataset = [['Apple', 'Banana', 'Egg'],
           ['Banana', 'Egg', 'Milk'],
           ['Apple', 'Banana'],
           ['Banana', 'Milk']]
```

```
# Convert dataset to one-hot encoded format
te = TransactionEncoder()
te_ary = te.fit(dataset).transform(dataset)
df = pd.DataFrame(te_ary, columns=te.columns_)
```

```
# Mining frequent itemsets using FP-Growth
frequent_itemsets = fpgrowth(df, min_support=0.3,
                             use_colnames=True)
```

```
# Display the frequent itemsets
print(frequent_itemsets)
```

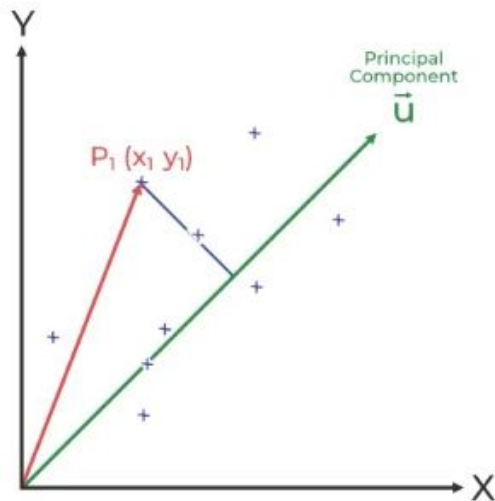


Dimensionality Reduction

A dark blue, diagonal shape that starts from the bottom left and extends towards the top right, covering the lower right portion of the slide. It has a smooth, slightly curved edge.

Principal Component Analysis

```
# Matrix multiplication or  
dot Product  
Z_pca = Z @ pca_component  
# Rename the columns name  
Z_pca.rename({'PC1':  
'PCA1', 'PC2': 'PCA2'},  
axis=1, inplace=True)  
# Print the Principal  
Component values  
print(Z_pca)
```



$$\begin{aligned}\text{Proj}_{P_1} \vec{u} &= \frac{P_1 \cdot \vec{u}}{|\vec{u}|} \\ &= P_1 \cdot \vec{u} \quad \dots \vec{u} \text{ --- Unit Vector}\end{aligned}$$

Singular Value Decomposition

Imports

```
from skimage.color import rgb2gray
from skimage import data
import matplotlib.pyplot as plt
import numpy as np
from scipy.linalg import svd
```

"""

SVD on image compression

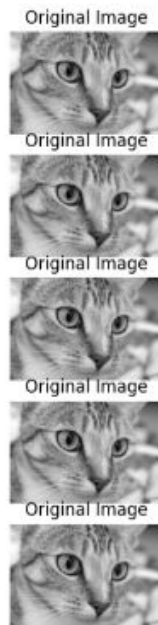
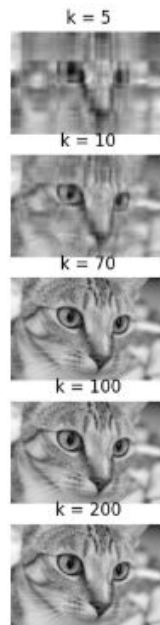
"""

```
cat = data.chelsea()
plt.imshow(cat)
# convert to grayscale
gray_cat = rgb2gray(cat)

# calculate the SVD and plot the image
U, S, V_T = svd(gray_cat, full_matrices=False)
S = np.diag(S)
fig, ax = plt.subplots(5, 2, figsize=(8, 20))
```

```
curr_fig = 0
```

```
for r in [5, 10, 70, 100, 200]:
    cat_approx = U[:, :r] @ S[0:r, :r] @ V_T[:, r, :]:]
    ax[curr_fig][0].imshow(cat_approx,
                           cmap='gray')
    ax[curr_fig][0].set_title("k = "+str(r))
    ax[curr_fig, 0].axis('off')
    ax[curr_fig][1].set_title("Original Image")
    ax[curr_fig][1].imshow(gray_cat,
                           cmap='gray')
    ax[curr_fig, 1].axis('off')
    curr_fig += 1
plt.show()
```

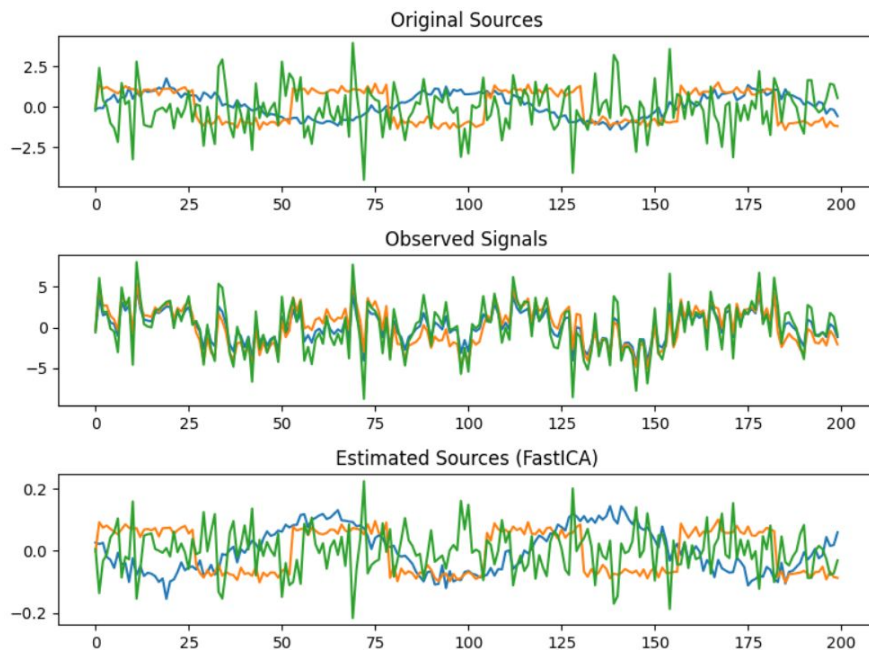


Independent Component Analysis

```
import numpy as np
from sklearn.decomposition import FastICA
import matplotlib.pyplot as plt
ica = FastICA(n_components=3)
S_ = ica.fit_transform(X) # Estimated sources
```

Plot the results

```
plt.figure(figsize=(8, 6))
plt.subplot(3, 1, 1)
plt.title('Original Sources')
plt.plot(S)
plt.subplot(3, 1, 2)
plt.title('Observed Signals')
plt.plot(X)
plt.subplot(3, 1, 3)
plt.title('Estimated Sources (FastICA)')
plt.plot(S_)
plt.tight_layout()
plt.show()
```



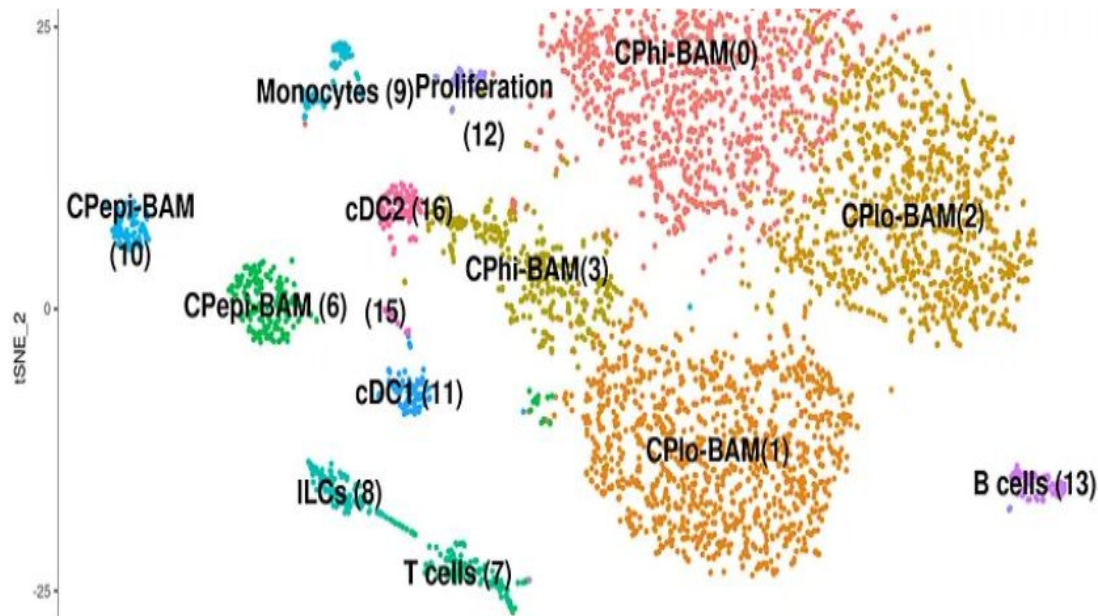
t-SNE

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.manifold import TSNE
from sklearn.preprocessing import StandardScaler
```

```
data_1000 = standardized_data[0:1000, :]
labels_1000 = labels[0:1000]
```

```
model = TSNE(n_components = 2, random_state = 0)
tsne_data = model.fit_transform(data_1000)
tsne_data = np.vstack((tsne_data.T, labels_1000)).T
tsne_df = pd.DataFrame(data = tsne_data, columns
= ("Dim_1", "Dim_2", "label"))
```

```
sn.scatterplot(data=tsne_df, x='Dim_1', y='Dim_2',
               hue='label', palette="bright")
plt.show()
```



UMAP

```
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns
import umap

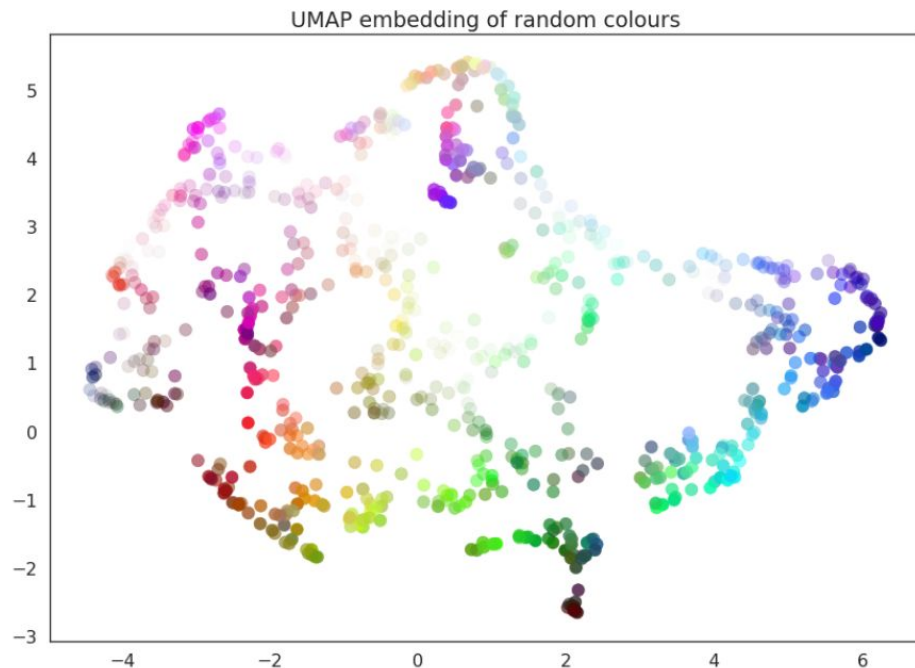
%matplotlib inline

fit = umap.UMAP()

%time u = fit.fit_transform(data)

CPU times: user 7.73 s, sys: 211 ms, total: 7.94 s
Wall time: 6.8 s

plt
plt.scatter(u[:,0],c=data)
plt.title('UMAP embedding of random colours');
```



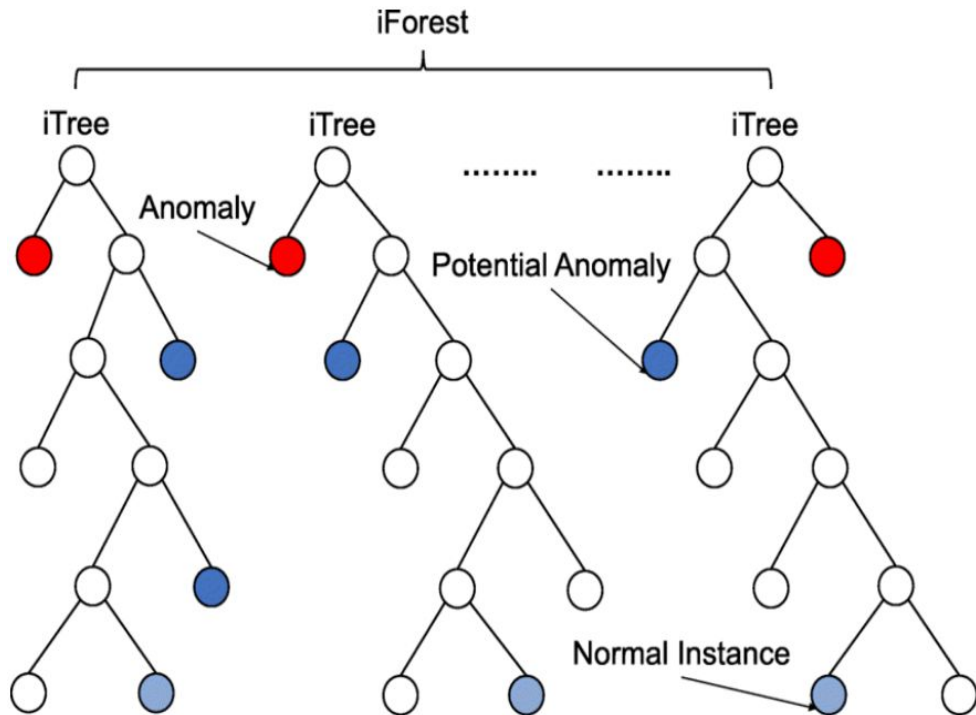
Anomaly Detection

A dark blue diagonal gradient bar that starts from the bottom left and extends towards the top right, covering the lower half of the slide.

Isolation Forest

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.ensemble import IsolationForest
```

```
df = pd.read_csv('salary.csv')
df.head(10)
model=IsolationForest(n_estimators=50,
max_samples='auto',
contamination=float(0.1),max_features=1.0)
model.fit(df[['salary']])
```



One – Class SVM

```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.font_manager
from sklearn import svm
%matplotlib inline
```

```
clf = svm.OneClassSVM()
clf.fit(X_train)
```