E6893 Big Data Analytics Lecture 4:

Big Data Analytics — Clustering and Classification

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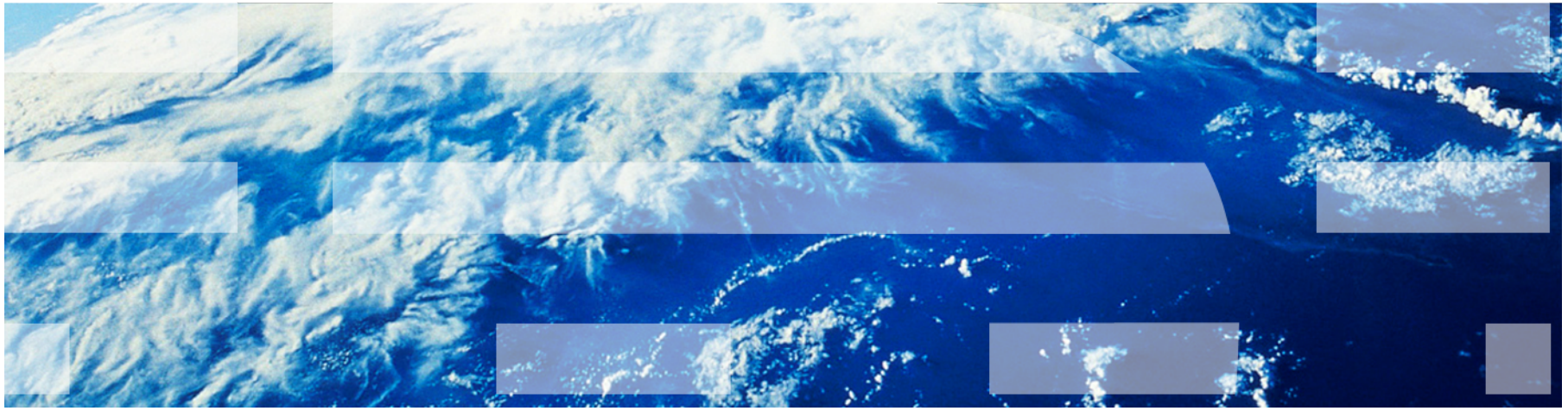


September 29th, 2016

Review — Key Components of Mahout

Collaborative Filtering

- User-Based Collaborative Filtering - single machine
- Item-Based Collaborative Filtering - **single machine** / MapReduce
- Matrix Factorization with Alternating Least Squares - **single machine** / MapReduce
- Matrix Factorization with Alternating Least Squares on Implicit Feedback- **single machine** / MapReduce
- Weighted Matrix Factorization, SVD++, Parallel SGD - **single machine**

Classification

- Logistic Regression - trained via SGD - single machine
- Naive Bayes/ Complementary Naive Bayes - MapReduce
- Random Forest - **MapReduce**
- Hidden Markov Models - single machine
- Multilayer Perceptron - **single machine**

Clustering

- Canopy Clustering - **single machine** / MapReduce (deprecated, will be removed once Streaming k-Means is stable enough)
- k-Means Clustering - single machine / MapReduce
- Fuzzy k-Means - single machine / MapReduce
- Streaming k-Means - single machine / MapReduce
- Spectral Clustering - MapReduce

Machine Learning example: using SVM to recognize a Toyota Camry

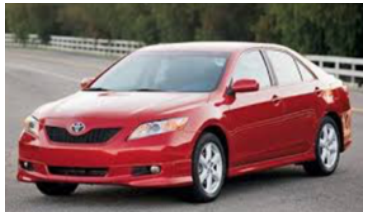
Non-ML

Rule 1.Symbol has something like bull's head
Rule 2.Big black portion in front of car.
Rule 3. …..????

ML — Support Vector Machine

Feature Space

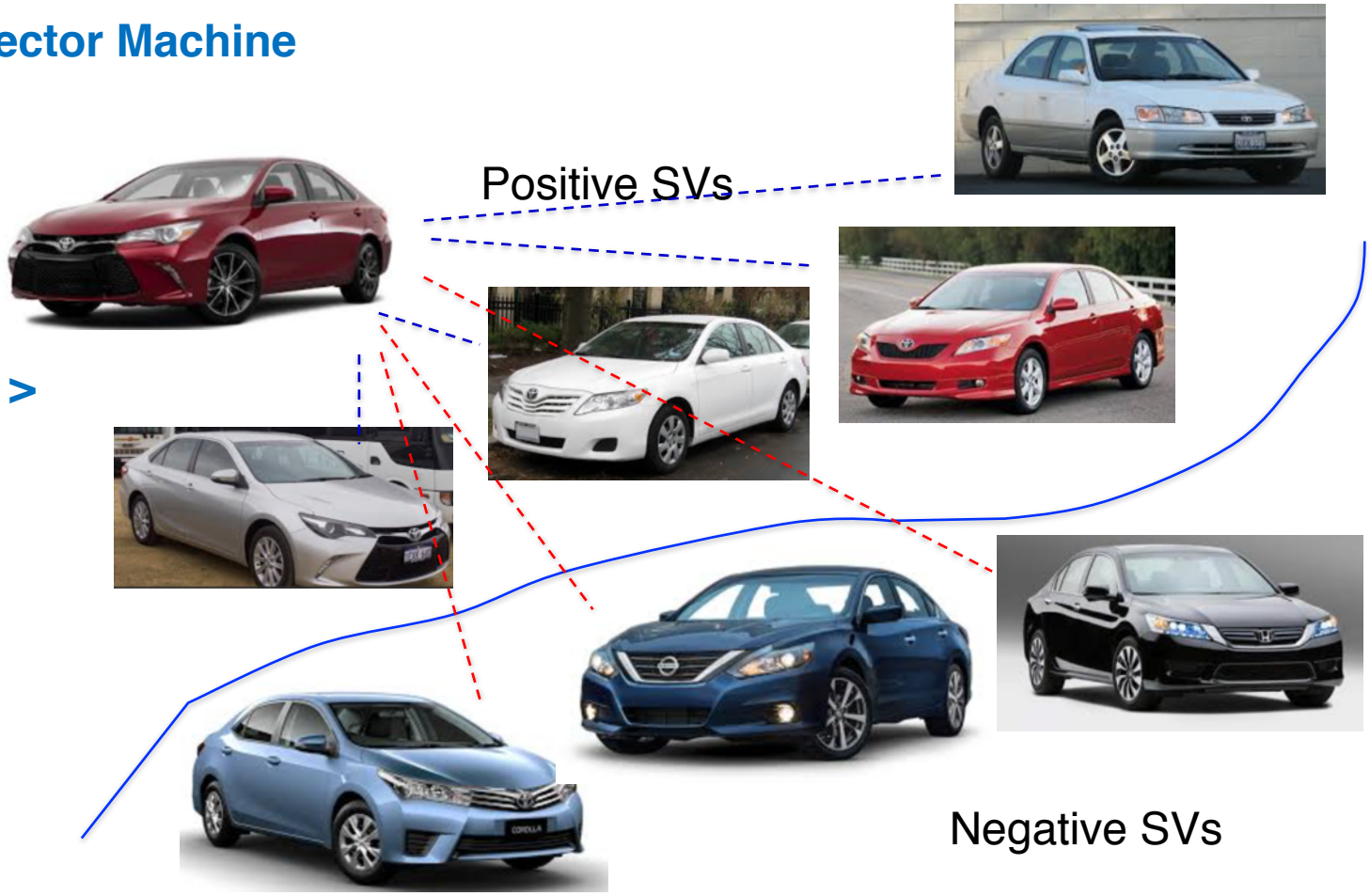
Positive SVs



Negative SVs

Machine Learning example: using SVM to recognize a Toyota Camry

ML — Support Vector Machine

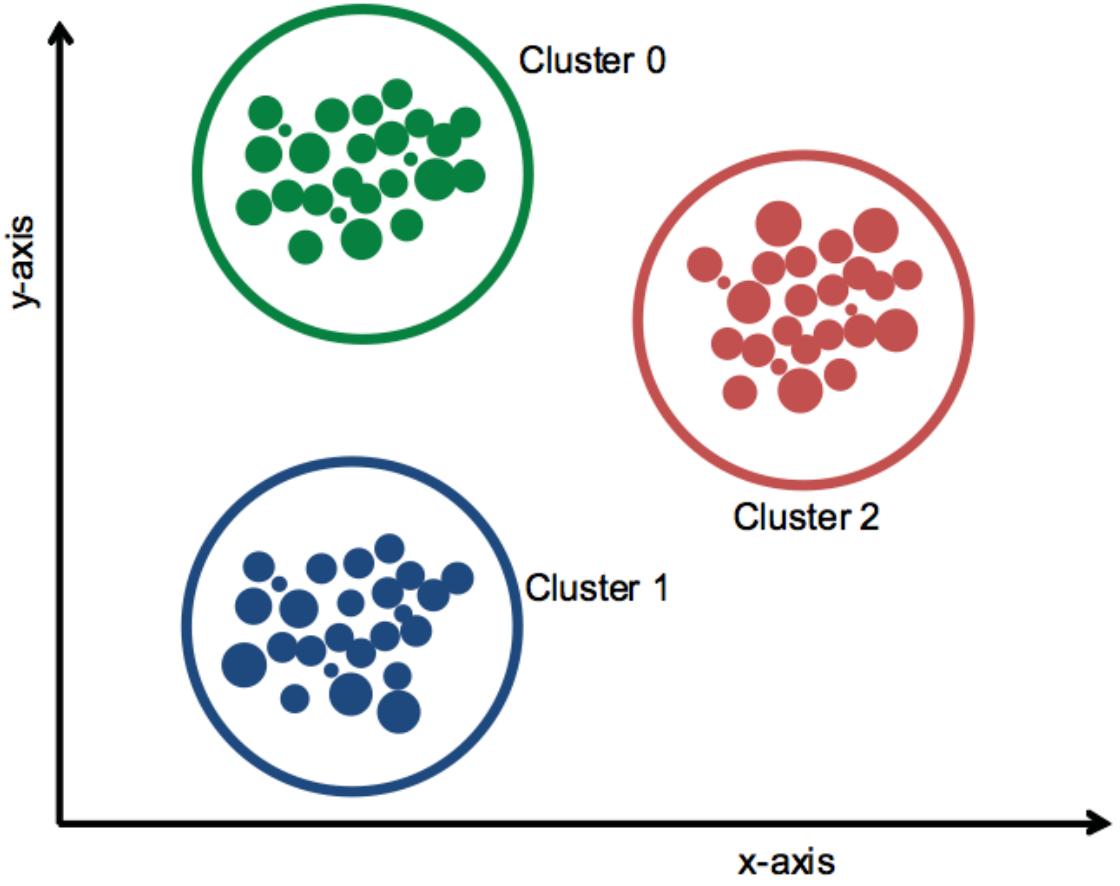


Clustering

Clustering a collection involves three things:

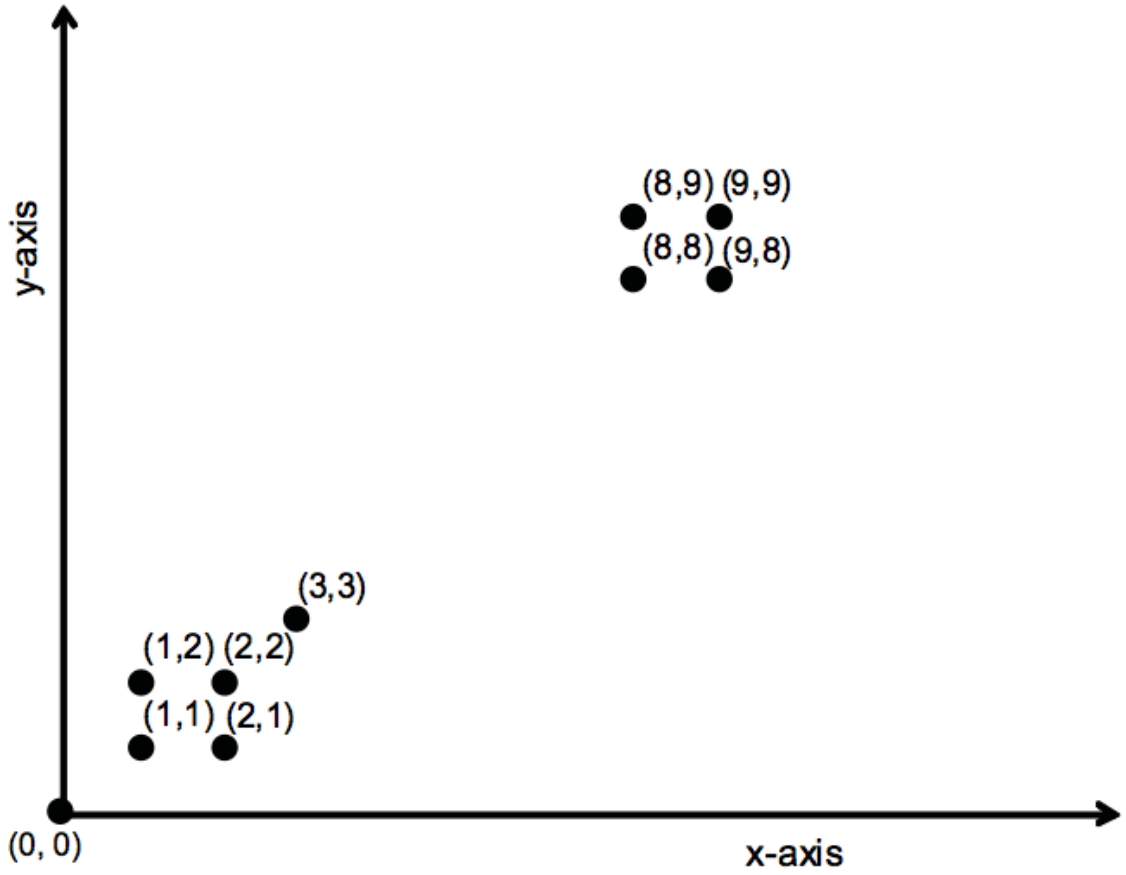
- *An algorithm*—This is the method used to group the books together.
- *A notion of both similarity and dissimilarity*—In the previous discussion, we relied on your assessment of which books belonged in an existing stack and which should start a new one.
- *A stopping condition*—In the library example, this might be the point beyond which books can't be stacked anymore, or when the stacks are already quite dissimilar.

Clustering — on feature plane

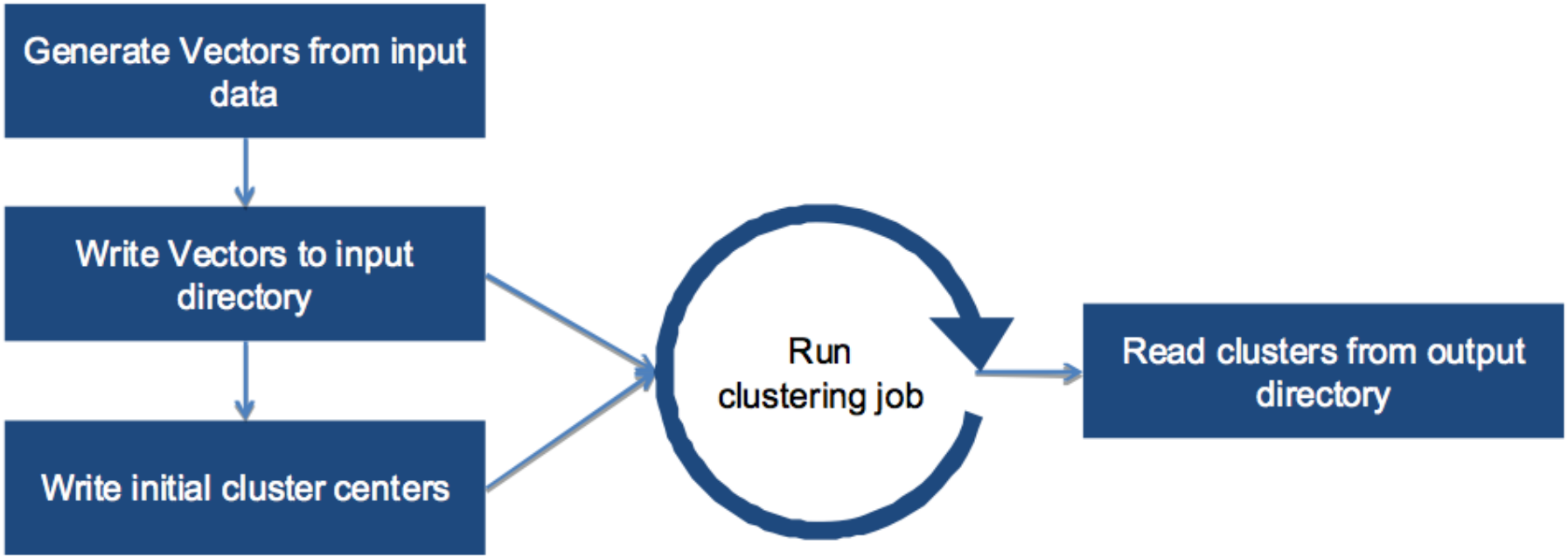


Clustering example

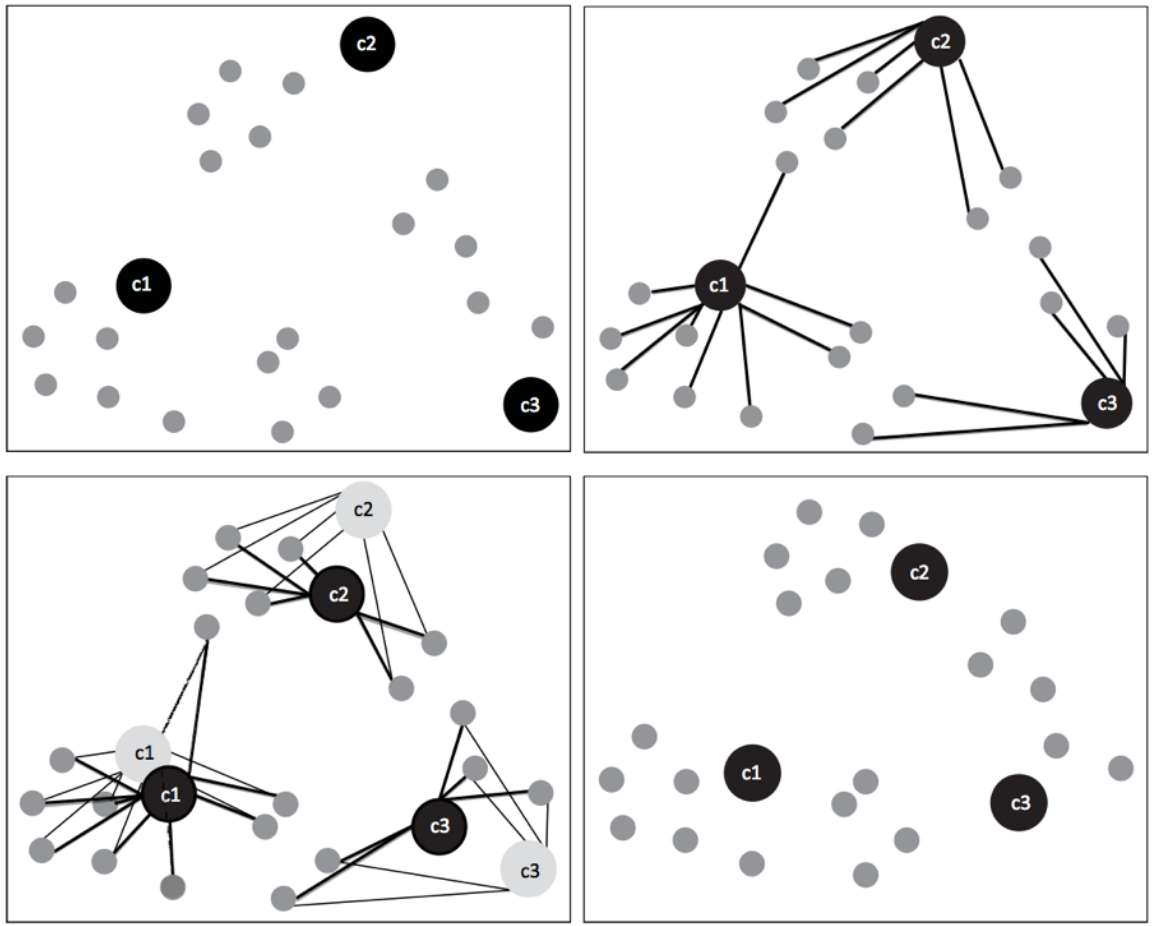
(1,1)
(2,1)
(1,2)
(2,2)
(3,3)
(8,8)
(8,9)
(9,8)
(9,9)



Steps on clustering

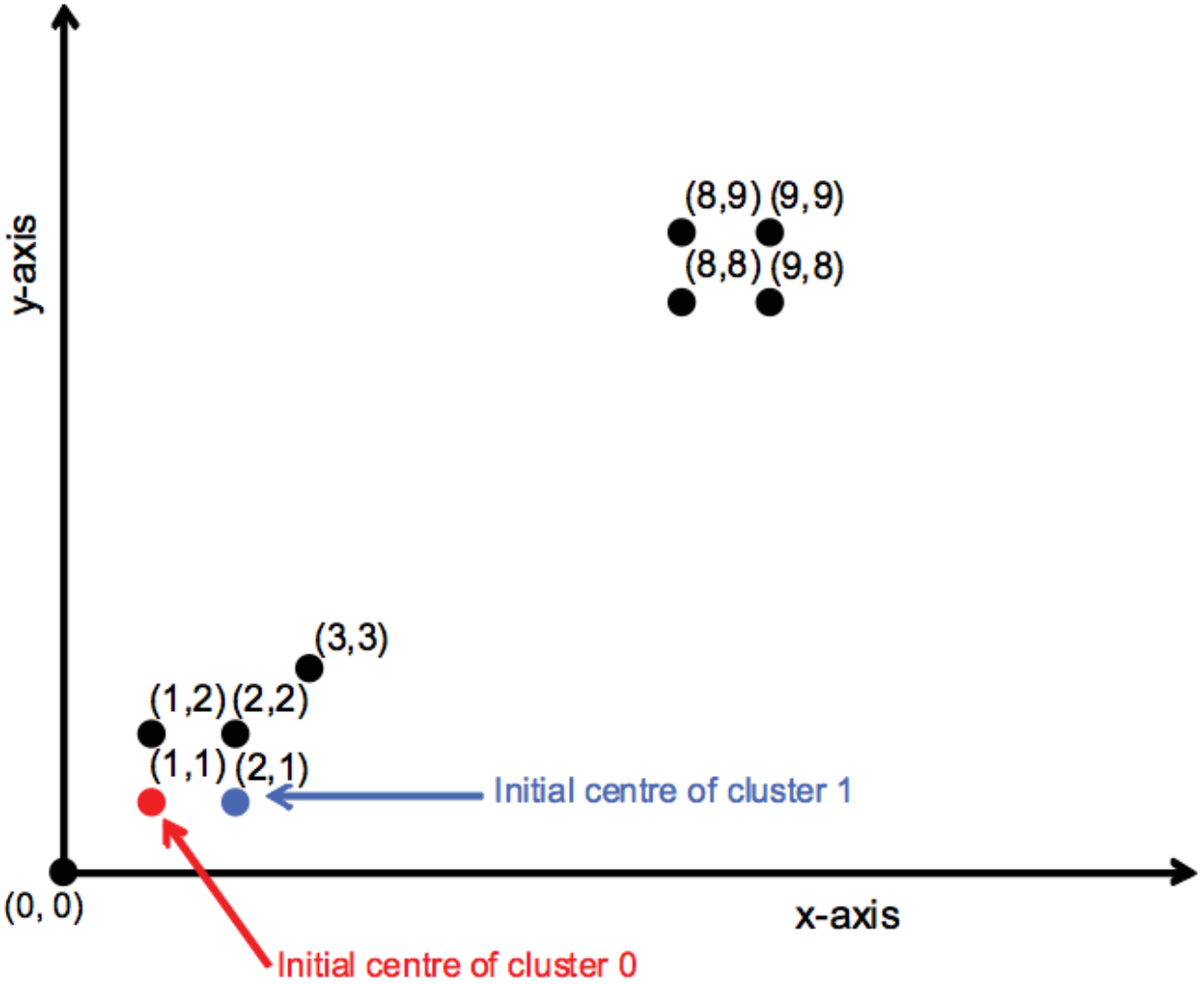


K-mean clustering



K-means clustering in action. Starting with three random points as centroids (top left), the map stage (top right) assigns each point to the cluster nearest to it. In the reduce stage (bottom left), the associated points are averaged out to produce the new location of the centroid, leaving you with the final configuration (bottom right). After each iteration, the final configuration is fed back into the same loop until the centroids come to rest at their final positions.

Making initial cluster centers



Parameters to Mahout k-mean clustering algorithm

- The `SequenceFile` containing the input vectors.
- The `SequenceFile` containing the initial cluster centers. In this case, we seed two clusters, so there are two centers.
- The similarity measure to be used. We use `EuclideanDistanceMeasure` as the measure of similarity here, and we explore other similarity measures later in this chapter.
- The `convergenceThreshold`. If in a particular iteration the centers of the clusters don't change beyond this threshold, no further iterations are done.
- The number of iterations to be done.
- The `Vector` implementation used in the input files.

HelloWorld clustering scenario

```
public static final double[][] points = { {1, 1}, {2, 1}, {1, 2},
                                          {2, 2}, {3, 3}, {8, 8},
                                          {9, 8}, {8, 9}, {9, 9}};

public static void writePointsToFile(List<Vector> points,
                                     String fileName,
                                     FileSystem fs,
                                     Configuration conf) throws IOException {
  Path path = new Path(fileName);
  SequenceFile.Writer writer = new SequenceFile.Writer(fs, conf,
      path, LongWritable.class, VectorWritable.class);
  long recNum = 0;
  VectorWritable vec = new VectorWritable();
  for (Vector point : points) {
    vec.set(point);
    writer.append(new LongWritable(recNum++), vec);
  }
  writer.close();
}

 public static List<Vector> getPoints(double[][] raw) {
   List<Vector> points = new ArrayList<Vector>();
   for (int i = 0; i < raw.length; i++) {
     double[] fr = raw[i];
     Vector vec = new RandomAccessSparseVector(fr.length);
     vec.assign(fr);
     points.add(vec);
   }
   return points;
 }
```

HelloWorld Clustering scenario - II

```
public static void main(String args[]) throws Exception {

  int k = 2;

  List<Vector> vectors = getPoints(points);

  File testData = new File("testdata");
  if (!testData.exists()) {
    testData.mkdir();
  }
  testData = new File("testdata/points");
  if (!testData.exists()) {
    testData.mkdir();
  }

  Configuration conf = new Configuration();
  FileSystem fs = FileSystem.get(conf);
  writePointsToFile(vectors,
      "testdata/points/file1", fs, conf);

  Path path = new Path("testdata/clusters/part-00000");
  SequenceFile.Writer writer
      = new SequenceFile.Writer(
          fs, conf,      path, Text.class, Cluster.class);

  for (int i = 0; i < k; i++) {
    Vector vec = vectors.get(i);
    Cluster cluster = new Cluster(
        vec, i, new EuclideanDistanceMeasure());
    writer.append(new Text(cluster.getIdentifier()), cluster);
  }
  writer.close();
```

Specify number of clusters to be formed

Create input directories for data

Write initial centers

HelloWorld Clustering scenario - III

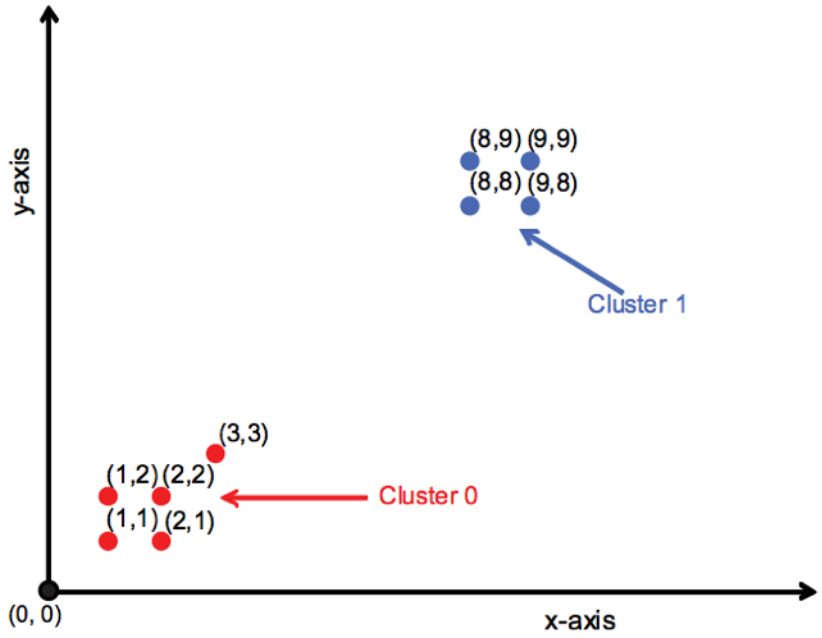
```
  KMeansDriver.run(conf, new Path("testdata/points"),
    new Path("testdata/clusters"),
    new Path("output"), new EuclideanDistanceMeasure(),
        0.001, 10, true, false);

  SequenceFile.Reader reader
      = new SequenceFile.Reader(fs,
          new Path("output/" + Cluster.CLUSTERED_POINTS_DIR
              + "/part-m-00000"), conf);

  IntWritable key = new IntWritable();
  WeightedVectorWritable value = new WeightedVectorWritable();
  while (reader.next(key, value)) {
    System.out.println(
        value.toString() + " belongs to cluster "
            + key.toString());
  }
  reader.close();
}
```

Run k-means algorithm

Read output, print vector, cluster ID

HelloWorld clustering scenario result

```
1.0: [1.000, 1.000] belongs to cluster 0
1.0: [2.000, 1.000] belongs to cluster 0
1.0: [1.000, 2.000] belongs to cluster 0
1.0: [2.000, 2.000] belongs to cluster 0
1.0: [3.000, 3.000] belongs to cluster 0
1.0: [8.000, 8.000] belongs to cluster 1
1.0: [9.000, 8.000] belongs to cluster 1
1.0: [8.000, 9.000] belongs to cluster 1
1.0: [9.000, 9.000] belongs to cluster 1
```



Testing difference distance measures

Euclidean distance measure

$$d = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \ldots + (a_n - b_n)^2}$$

Squared Euclidean distance measure

$$d = (a_1 - b_1)^2 + (a_2 - b_2)^2 + \ldots + (a_n - b_n)^2$$

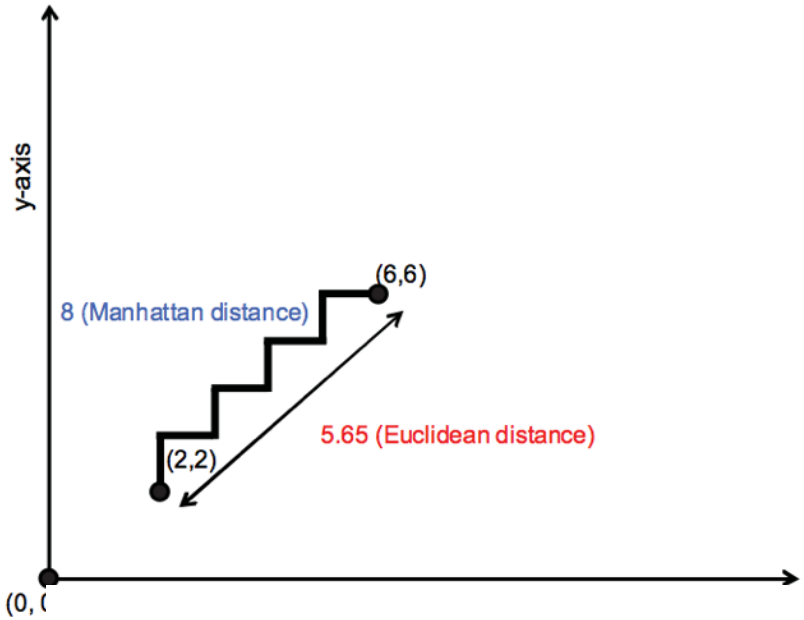
Manhattan distance measure

$$d = |a_1 - b_1| + |a_2 - b_2| + \ldots + |a_n - b_n|$$

Manhattan and Cosine distances

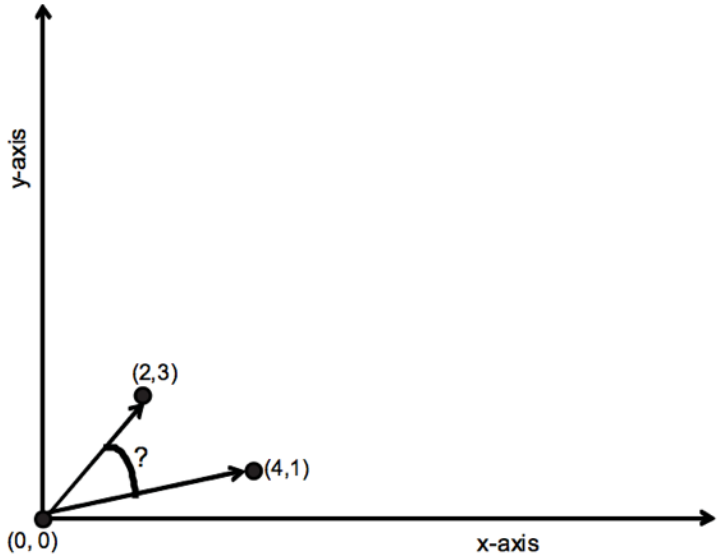
Manhattan distance measure

$$d = |a_1 - b_1| + |a_2 - b_2| + \ldots + |a_n - b_n|$$



Cosine distance measure

$$d = 1 - \frac{(a_1 b_1 + a_2 b_2 + \ldots + a_n b_n)}{(\sqrt{(a_1^2 + a_2^2 + \ldots + a_n^2)}\sqrt{(b_1^2 + b_2^2 + \ldots + b_n^2)})}$$



Tanimoto distance measure

$$d = 1 - \frac{(a_1 b_1 + a_2 b_2 + \ldots + a_n b_n)}{\sqrt{(a_1^2 + a_2^2 + \ldots + a_n^2)} + \sqrt{(b_1^2 + b_2^2 + \ldots + b_n^2)} - (a_1 b_1 + a_2 b_2 + \ldots + a_n b_n)}$$

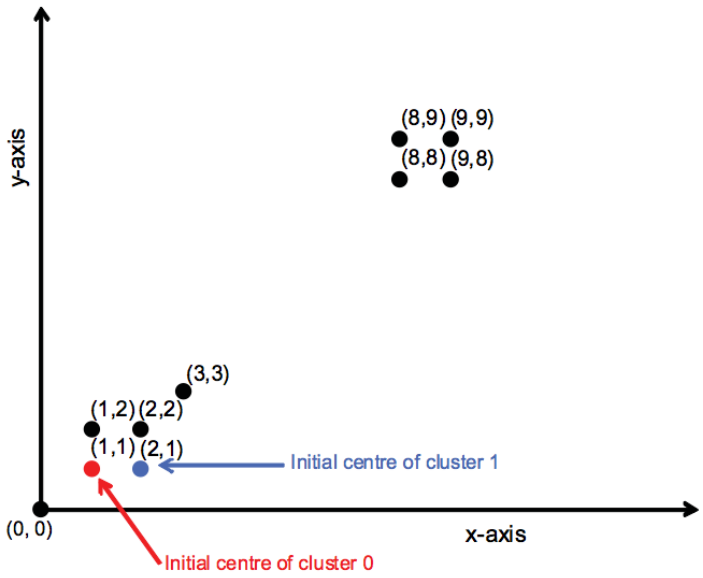
Weighted distance measure

Mahout also provides a `WeightedDistanceMeasure` class, and implementations of Euclidean and Manhattan distance measures that use it. A weighted distance measure is an advanced feature in Mahout that allows you to give weights to different dimensions in order to either increase or decrease the effect of a dimension

Results comparison

Distance measure	Number of iterations	Vectors[a] in cluster 0	Vectors in cluster 1
EuclideanDistanceMeasure	3	0, 1, 2, 3, 4	5, 6, 7, 8
SquaredEuclideanDistanceMeasure	5	0, 1, 2, 3, 4	5, 6, 7, 8
ManhattanDistanceMeasure	3	0, 1, 2, 3, 4	5, 6, 7, 8
CosineDistanceMeasure	1	1	0, 2, 3, 4, 5, 6, 7, 8
TanimotoDistanceMeasure	3	0, 1, 2, 3, 4	5, 6, 7, 8

(1,1)
(2,1)
(1,2)
(2,2)
(3,3)
(8,8)
(8,9)
(9,8)
(9,9)

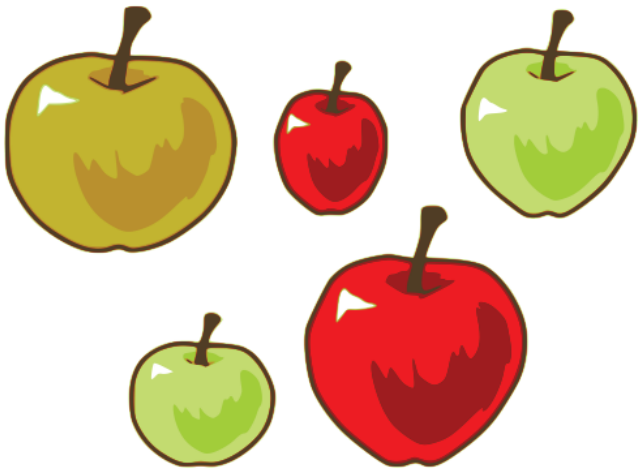


Data preparation in Mahout — vectors

In Mahout, vectors are implemented as three different classes, each of which is optimized for different scenarios: `DenseVector`, `RandomAccessSparseVector`, and `SequentialAccessSparseVector`.

- `DenseVector` can be thought of as an array of doubles, whose size is the number of features in the data. Because all the entries in the array are preallocated regardless of whether the value is 0 or not, we call it *dense*.
- `RandomAccessSparseVector` is implemented as a `HashMap` between an `integer` and a `double`, where only nonzero valued features are allocated. Hence, they're called as `SparseVectors`.
- `SequentialAccessSparseVector` is implemented as two parallel arrays, one of integers and the other of doubles. Only nonzero valued entries are kept in it. Unlike the `RandomAccessSparseVector`, which is optimized for random access, this one is optimized for linear reading.

vectorization example



0: weight
1: color
2: size

```
[0 => 100 gram, 1 => red, 2 => small]
```

Apple	Weight (kg) (0)	Color (1)	Size (2)	Vector
Small, round, green	0.11	510	1	[0.11, 510, 1]
Large, oval, red	0.23	650	3	[0.23, 650, 3]
Small, elongated, red	0.09	630	1	[0.09, 630, 1]
Large, round, yellow	0.25	590	3	[0.25, 590, 3]
Medium, oval, green	0.18	520	2	[0.18, 520, 2]

Mahout codes to create vectors of the apple example

```
public static void main(String args[]) throws Exception {
  List<NamedVector> apples = new ArrayList<NamedVector>();

  NamedVector apple;
  apple = new NamedVector(
      new DenseVector(new double[] {0.11, 510, 1}),
      "Small round green apple");
  apples.add(apple);
  apple = new NamedVector(
    new DenseVector(new double[] {0.23, 650, 3}),
      "Large oval red apple");
  apples.add(apple);
  apple = new NamedVector(
    new DenseVector(new double[] {0.09, 630, 1}),
      "Small elongated red apple");
  apples.add(apple);
  apple = new NamedVector(
    new DenseVector(new double[] {0.25, 590, 3}),
      "Large round yellow apple");
  apples.add(apple);
  apple = new NamedVector(
    new DenseVector(new double[] {0.18, 520, 2}),
      "Medium oval green apple");
```

Associates a name with the vector

Mahout codes to create vectors of the apple example — II

```
Configuration conf = new Configuration();
FileSystem fs = FileSystem.get(conf);

Path path = new Path("appledata/apples");
SequenceFile.Writer writer = new SequenceFile.Writer(fs, conf,
    path, Text.class, VectorWritable.class);
VectorWritable vec = new VectorWritable();
for (NamedVector vector : apples) {
  vec.set(vector);
  writer.append(new Text(vector.getName()), vec);
}
writer.close();

SequenceFile.Reader reader = new SequenceFile.Reader(fs,
    new Path("appledata/apples"), conf);

Text key = new Text();
VectorWritable value = new VectorWritable();
while (reader.next(key, value)) {

  System.out.println(key.toString() + " "
      + value.get().asFormatString());
}
reader.close();
}
```

Serializes vector data

Deserializes vector data

Vectorization of text

Vector Space Model: Term Frequency (TF)

For example, if the word *horse* is assigned to the 39,905th index of the vector, the word *horse* will correspond to the 39,905th dimension of document vectors. A document's vectorized form merely consists, then, of the number of times each word occurs in the document, and that value is stored in the vector along that word's dimension. The dimension of these document vectors can be very large.

Stop Words: *a, an, the, who, what, are, is, was,* and so on.

Stemming:

A stemmer for English, for example, should identify the string "cats" (and possibly "catlike", "catty" etc.) as based on the root "cat", and "stemmer", "stemming", "stemmed" as based on "stem". A stemming algorithm reduces the words "fishing", "fished", and "fisher" to the root word, "fish". On the other hand, "argue", "argued", "argues", "arguing", and "argus" reduce to the stem "argu" (illustrating the case where the stem is not itself a word or root) but "argument" and "arguments" reduce to the stem "argument".

Most Popular Stemming algorithms

Columbia University

Lookup algorithms

A simple stemmer looks up the inflected form in a lookup table. The advantages of this approach is that it is simple, fast, and easily handles exceptions. The disadvantages are that all inflected forms must be explicitly listed in the table: new or unfamiliar words are not handled, even if they are perfectly regular (e.g. iPads ~ iPad), and the table may be large. For languages with simple morphology, like English, table sizes are modest, but

Suffix-stripping algorithms

Suffix stripping algorithms do not rely on a lookup table that consists of inflected forms and root form relations. Instead, a typically smaller list of "rules" is stored which provides a path for the algorithm, given an input word form, to find its root form. Some examples of the rules include:

- if the word ends in 'ed', remove the 'ed'
- if the word ends in 'ing', remove the 'ing'
- if the word ends in 'ly', remove the 'ly'

Term Frequency — Inverse Document Frequency (TF-IDF)

The value of word is reduced more if it is used frequently across all the documents in the dataset.

To calculate the inverse document frequency, the document frequency (DF) for each word is first calculated. Document frequency is the number of documents the word occurs in. The number of times a word occurs in a document isn't counted in document frequency. Then, the inverse document frequency or IDF_i for a word, w_i, is

$$IDF_i = \frac{1}{DF_i}$$

$$W_i = TF_i \cdot IDF_i = TF_i \cdot \frac{N}{DF_i} \quad \text{or} \quad W_i = TF_i \cdot \log \frac{N}{DF_i}$$

n-gram

It was the best of time. it was the worst of times. ==>
bigram

It was
was the
the best
best of
of times
times it
it was
was the
the worst
worst of
of times

Mahout provides a log-likelihood test to reduce the dimensions of n-grams

Examples — using a news corpus

Reuters-21578 dataset: 22 files, each one has 1000 documents except the last one.

http://www.daviddlewis.com/resources/testcollections/ reuters21578/

Extraction code:

```
mvn -e -q exec:java
-Dexec.mainClass="org.apache.lucene.benchmark.utils.ExtractReuters"
-Dexec.args="reuters/ reuters-extracted/"
```

Using the extracted folder, run the `SequenceFileFromDirectory` class. You can use the launcher script from the Mahout root directory to do the same:

```
bin/mahout seqdirectory -c UTF-8
-i examples/reuters-extracted/ -o reuters-seqfiles
```

This will write the Reuters articles in the `SequenceFile` format. Now the only step left is to convert this data to vectors. To do that, run the `SparseVectorsFromSequence-Files` class using the Mahout launcher script:

```
bin/mahout seq2sparse -i reuters-seqfiles/ -o reuters-vectors -ow
```

Mahout dictionary-based vectorizer

Option	Flag	Description	Default value
Overwrite (bool)	-ow	If set, the output folder is overwritten. If not set, the output folder is created if the folder doesn't exist. If the output folder does exist, the job fails and an error is thrown. Default is unset.	N/A
Lucene analyzer name (String)	-a	The class name of the analyzer to use.	org.apache.lucene .analysis.standard .StandardAnalyzer
Chunk size (int)	-chunk	The chunk size in MB. For large document collections (sizes in GBs and TBs), you won't be able to load the entire dictionary into memory during vectorization, so you can split the dictionary into chunks of the specified size and perform the vectorization in multiple stages. It's recommended you keep this size to 80 percent of the Java heap size of the Hadoop child nodes to prevent the vectorizer from hitting the heap limit.	100
Weighting (String)	-wt	The weighting scheme to use: tf for term-frequency based weighting and tfidf for TF-IDF based weighting.	tfidf
Minimum support (int)	-s	The minimum frequency of the term in the entire collection to be considered as a part of the dictionary file. Terms with lesser frequency are ignored.	2

Mahout dictionary-based vectorizer — II

Option	Flag	Description	Default value
Minimum document frequency (int)	-md	The minimum number of documents the term should occur in to be considered a part of the dictionary file. Any term with lesser frequency is ignored.	1
Max document frequency percentage (int)	-x	The maximum number of documents the term should occur in to be considered a part of the dictionary file. This is a mechanism to prune out high frequency terms (stop-words). Any word that occurs in more than the specified percentage of documents is ignored.	99
N-gram size (int)	-ng	The maximum size of n-grams to be selected from the collection of documents.	1

Mahout dictionary-based vectorizer — III

Option	Flag	Description	Default value
Minimum log-likelihood ratio (LLR) (`float`)	`-ml`	This flag works only when n-gram size is greater than 1. Very significant n-grams have large scores, such as 1000; less significant ones have lower scores. Although there's no specific method for choosing this value, the rule of thumb is that n-grams with a LLR value less than 1.0 are irrelevant.	`1.0`
Normalization (`float`)	`-n`	The normalization value to use in the L_p space. A detailed explanation of normalization is given in section 8.4. The default scheme is to not normalize the weights.	`0`
Number of reducers (`int`)	`-nr`	The number of reducer tasks to execute in parallel. This flag is useful when running a dictionary vectorizer on a Hadoop cluster. Setting this to the maximum number of nodes in the cluster gives maximum performance. Setting this value higher than the number of cluster nodes leads to a slight decrease in performance. For more details, read the Hadoop documentation on setting the optimum number of reducers.	`1`
Create sequential access sparse vectors (`bool`)	`-seq`	If set, the output vectors are created as `SequentialAccessSparseVectors`. By default the dictionary vectorizer generates `RandomAccessSparseVectors`. The former gives higher performance on certain algorithms like k-means and SVD due to the sequential nature of vector operations. By default the flag is unset.	N/A

Outputs & Steps

```
$ ls reuters-vectors/
df-count/
dictionary.file-0
frequency.file-0
tfidf-vectors/
tf-vectors/
tokenized-documents/

wordcount/
```

1. Tokenization using Lucene StandardAnalyzer
2. n-gram generation step
3. converts the tokenized documents into vectors using TF
4. count DF and then create TF-IDF

A practical setting of flags

- `-a`—Use `org.apache.lucene.analysis.WhitespaceAnalyzer` to tokenize words based on the whitespace characters between them.
- `-chunk`—Use a chunk size of 200 MB. This value won't produce any effect on the Reuters data, because the dictionary sizes are usually in the 1 MB range.
- `-wt`—Use the `tfidf` weighting method.
- `-s`—Use a minimum support value of `5`.
- `-md`—Use a minimum document frequency value of `3`.
- `-x`—Use a maximum document frequency percentage of 90 percent to aggressively prune away high-frequency words.
- `-ng`—Use an *n*-gram size of `2` to generate both unigrams and bigrams.
- `-ml`—Use a minimum log-likelihood ratio (LLR) value of `50` to keep only very significant bigrams.
- `-seq`—Set the `SequentialAccessSparseVectors` flag.

Run the vectorizer using the preceding options in the Mahout launcher script:

```
bin/mahout seq2sparse -i reuters-seqfiles/ -o reuters-vectors-bigram -ow
-a org.apache.lucene.analysis.WhitespaceAnalyzer
-chunk 200 -wt tfidf -s 5 -md 3 -x 90 -ng 2 -ml 50 -seq
```

normalization

Some documents may pop up showing they are similar to all the other documents because it is large. ==> Normalization can help.

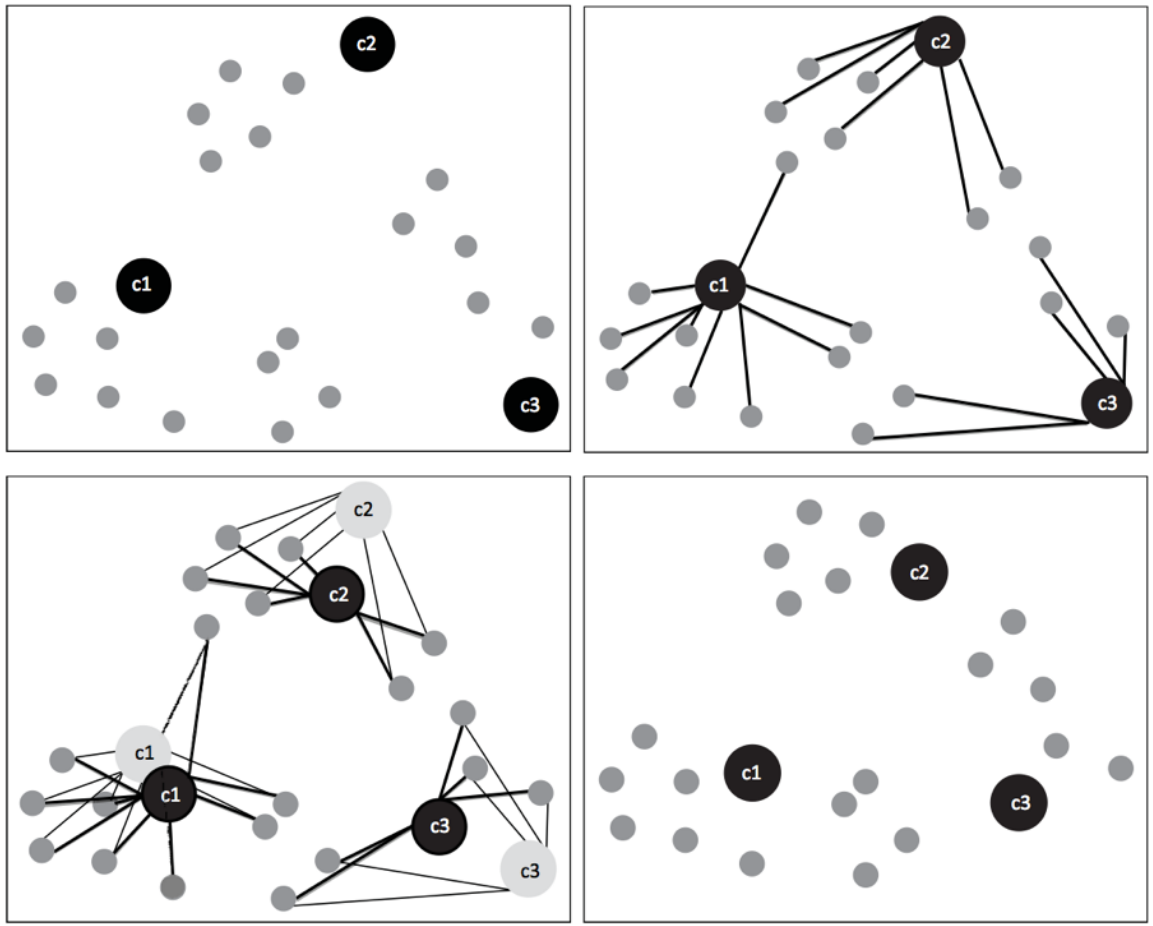
In Mahout, normalization uses what is known in statistics as a *p*-norm. For example, the *p*-norm of a 3-dimensional vector, [x, y, z], is

$$\frac{x}{(|x|^p + |y|^p + |z|^p)^{1/p}}, \frac{y}{(|x|^p + |y|^p + |z|^p)^{1/p}}, \frac{z}{(|x|^p + |y|^p + |z|^p)^{1/p}}$$

Clustering methods provided by Mahout

- K-means clustering
- Centroid generation using canopy clustering
- Fuzzy k-means clustering and Dirichlet clustering
- Topic modeling using latent Dirichlet allocation as a variant of clustering

K-mean clustering



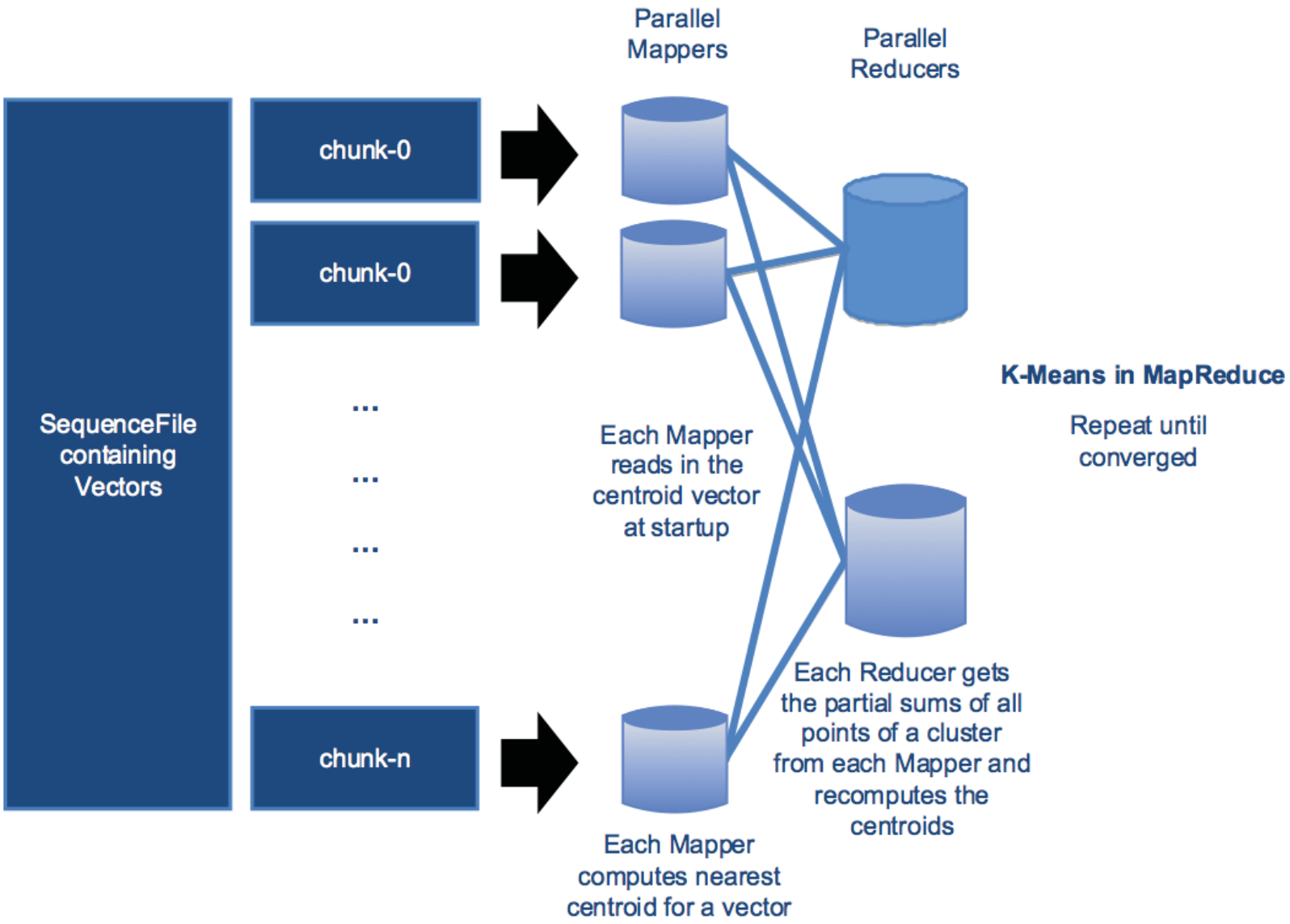
K-means clustering in action. Starting with three random points as centroids (top left), the map stage (top right) assigns each point to the cluster nearest to it. In the reduce stage (bottom left), the associated points are averaged out to produce the new location of the centroid, leaving you with the final configuration (bottom right). After each iteration, the final configuration is fed back into the same loop until the centroids come to rest at their final positions.

Hadoop k-mean clustering jobs

In Mahout, the MapReduce version of the k-means algorithm is instantiated using the `KMeansDriver` class. The class has just a single entry point—the `runJob` method.

- The Hadoop configuration.
- The `SequenceFile` containing the input `Vectors`.
- The `SequenceFile` containing the initial `Cluster` centers.
- The similarity measure to be used. We'll use `EuclideanDistanceMeasure` as the measure of similarity and experiment with the others later.
- The `convergenceThreshold`. If in an iteration, the centroids don't move more than this distance, no further iterations are done and clustering stops.
- The number of iterations to be done. This is a hard limit; the clustering stops if this threshold is reached.

K-mean clustering running as MapReduce job



Hadoop k-mean clustering code

```
KmeansDriver.runJob(hadoopConf,
      inputVectorFilesDirPath, clusterCenterFilesDirPath,
      outputDir, new EuclideanDistanceMeasure(),
      convergenceThreshold, numIterations, true, false);
```

Mahout reads and writes data using the Hadoop `FileSystem` class. This provides seamless access to both the local filesystem (via java.io) and distributed filesystems like HDFS and S3FS (using internal Hadoop classes). This way, the same code that works on the local system will also work on the Hadoop filesystem on the cluster, provided the paths to the Hadoop configuration files are correctly set in the environment variables. In Mahout, the bin/mahout shell script finds the Hadoop configuration files automatically from the `$HADOOP_CONF` environment variable.

```
$ bin/mahout kmeans -i reuters-vectors/tfidf-vectors/ \
-c reuters-initial-clusters  \
-o reuters-kmeans-clusters \
-dm org.apache.mahout.common.distance.SquaredEuclideanDistanceMeasure \
-cd 1.0 -k 20 -x 20 -cl
```

The output

The directory listing of the output folder looks something like this:

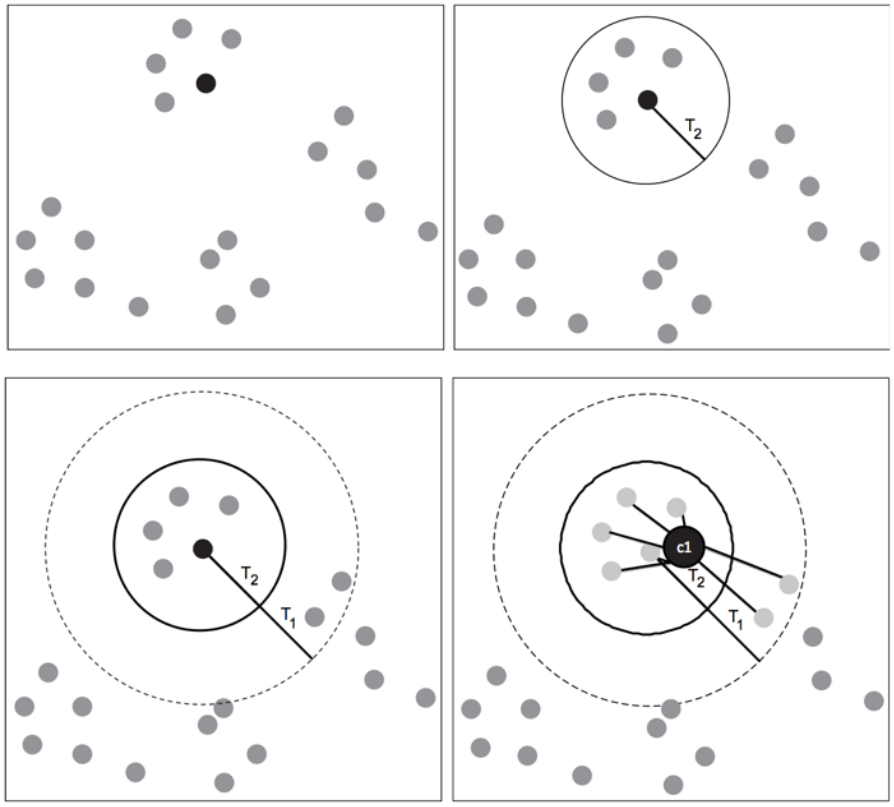
```
$ ls -l reuters-kmeans-clusters
drwxr-xr-x  4 user  5000  136 Feb 1 18:56 clusters-0
drwxr-xr-x  4 user  5000  136 Feb 1 18:56 clusters-1
drwxr-xr-x  4 user  5000  136 Feb 1 18:56 clusters-2
...
drwxr-xr-x  4 user  5000  136 Feb 1 18:59 clusteredPoints

$ bin/mahout clusterdump -dt sequencefile \
-d reuters-vectors/dictionary.file-* \
-s  reuters-kmeans-clusters/clusters-19 -b 10 -n 10
```

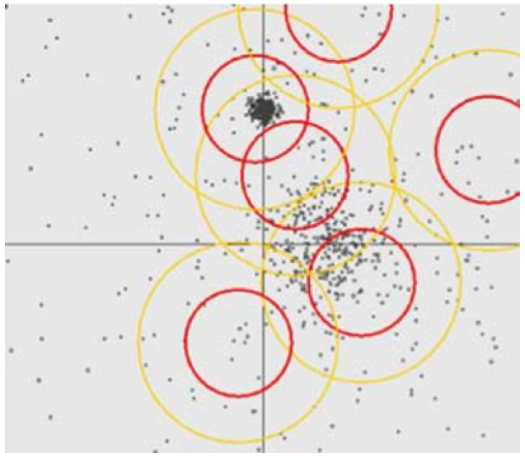
Running `ClusterDumper` on the output folder corresponding to the last iteration produces output similar to the following:

```
Id: 11736:
    Top Terms: debt, banks, brazil, bank, billion, he, payments, billion
     dlrs, interest, foreign

Id: 11235:
    Top Terms: amorphous, magnetic, metals, allied signal, 19.39, corrosion,
     allied, molecular, mode, electronic components
...
Id: 20073:
    Top Terms: ibm, computers, computer, att, personal, pc, operating system,
     intel, machines, dos
```

Canopy clustering to estimate the number of clusters

Tell what size clusters to look for. The algorithm will find the number of clusters that have approximately that size. The algorithm uses two distance thresholds. This method prevents all points close to an already existing canopy from being the center of a new canopy.





Canopy clustering: if you start with a point (top left) and mark it as part of a canopy, all the points within distance T_2 (top right) are removed from the data set and prevented from becoming new canopies. The points within the outer circle (bottom-right) are also put in the same canopy, but they're allowed to be part of other canopies. This assignment process is done in a single pass on a mapper. The reducer computes the average of the centroid (bottom right) and merges close canopies.

Running canopy clustering

To run canopy generation over the Reuters data set, execute the canopy program using the Mahout launcher as follows:

```
$ bin/mahout canopy -i reuters-vectors/tfidf-vectors \
-o reuters-canopy-centroids \
-dm org.apache.mahout.common.distance.EuclideanDistanceMeasure \
-t1 1500 -t2 2000
```

Within a minute, CanopyDriver will generate the centroids in the output folder.

Created less than 50 centroids.

```
$ bin/mahout kmeans -i reuters-vectors/tfidf-vectors \
-o reuters-kmeans-clusters \
-dm org.apache.mahout.common.distance.TanimotoDistanceMeasure  \
-c reuters-canopy-centroids/clusters-0 -cd 0.1 -ow -x 20 -cl
```

After the clustering is done, use ClusterDumper to inspect the clusters. Some of them are listed here:

```
Id: 21523:name:
    Top Terms:
tones, wheat, grain, said, usda, corn, us, sugar, export, agriculture
Id: 21409:name:
    Top Terms:
stock, share, shares, shareholders, dividend, said, its, common, board,
     company
Id: 21155:name:
    Top Terms:
oil, effective, crude, raises, prices, barrel, price, cts, said, dlrs
Id: 19658:name:
    Top Terms:
drug, said, aids, inc, company, its, patent, test, products, food
Id: 21323:name:
    Top Terms:
       7-apr-1987, 11, 10, 12, 07, 09, 15, 16, 02, 17
```

News clustering code

```
public class NewsKMeansClustering {
  public static void main(String args[]) throws Exception {
    int minSupport = 2;
    int minDf = 5;
    int maxDFPercent = 95;
    int maxNGramSize = 2;
    int minLLRValue = 50;
    int reduceTasks = 1;
    int chunkSize = 200;
    int norm = 2;
    boolean sequentialAccessOutput = true;

    String inputDir = "inputDir";

    Configuration conf = new Configuration();
    FileSystem fs = FileSystem.get(conf);

    String outputDir = "newsClusters";
    HadoopUtil.delete(new Path(outputDir));
    Path tokenizedPath = new Path(outputDir,
        DocumentProcessor.TOKENIZED_DOCUMENT_OUTPUT_FOLDER);
    MyAnalyzer analyzer = new MyAnalyzer();
```

Custom Lucene Analyzer

News clustering example —> finding related articles

News clustering code — II

```
DocumentProcessor.tokenizeDocuments(new Path(inputDir),
  analyzer.getClass().asSubclass(Analyzer.class),
  tokenizedPath, conf);

DictionaryVectorizer.createTermFrequencyVectors(tokenizedPath,
  new Path(outputDir), conf, minSupport, maxNGramSize, minLLRValue,
  2, true, reduceTasks,
  chunkSize, sequentialAccessOutput, false);
TFIDFConverter.processTfIdf(
  new Path(outputDir ,
 DictionaryVectorizer.DOCUMENT_VECTOR_OUTPUT_FOLDER),
  new Path(outputDir), conf, chunkSize, minDf,
  maxDFPercent, norm, true, sequentialAccessOutput, false,
 reduceTasks);
Path vectorsFolder = new Path(outputDir, "tfidf-vectors");
Path canopyCentroids = new Path(outputDir ,
                                "canopy-centroids");
Path clusterOutput = new Path(outputDir , "clusters");

CanopyDriver.run(vectorsFolder, canopyCentroids,
  new EuclideanDistanceMeasure(), 250, 120,
  false, false);
KMeansDriver.run(conf, vectorsFolder,
  new Path(canopyCentroids, "clusters-0"),
  clusterOutput, new TanimotoDistanceMeasure(), 0.01,
  20, true, false);
```

Tokenize text

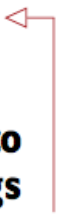
Calculate TF-IDF vectors

Run canopy centroid generation

Run k-means algorithm

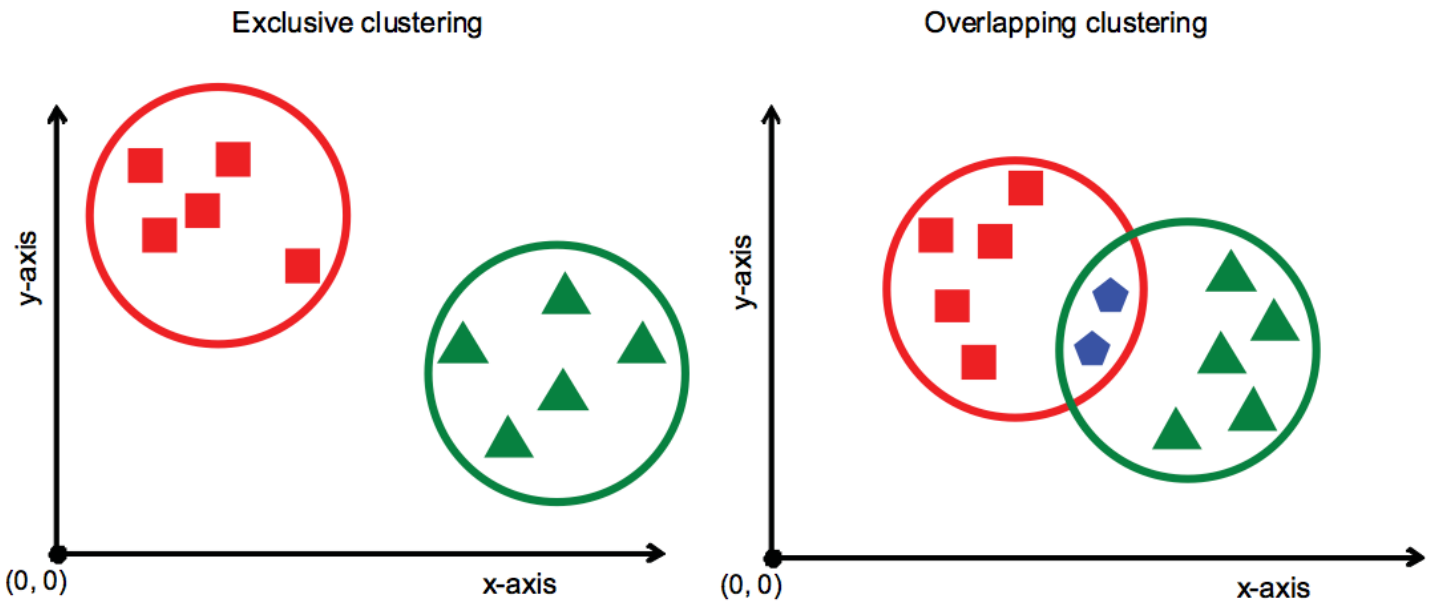
News clustering code — III

```
    SequenceFile.Reader reader = new SequenceFile.Reader(fs,
        new Path(clusterOutput
            + Cluster.CLUSTERED_POINTS_DIR + "/part-00000"), conf);

    IntWritable key = new IntWritable();
    WeightedVectorWritable value = new WeightedVectorWritable();
    while (reader.next(key, value)) {
       System.out.println(key.toString() + " belongs to cluster "
       + value.toString());
    }
    reader.close();
  }
}
```

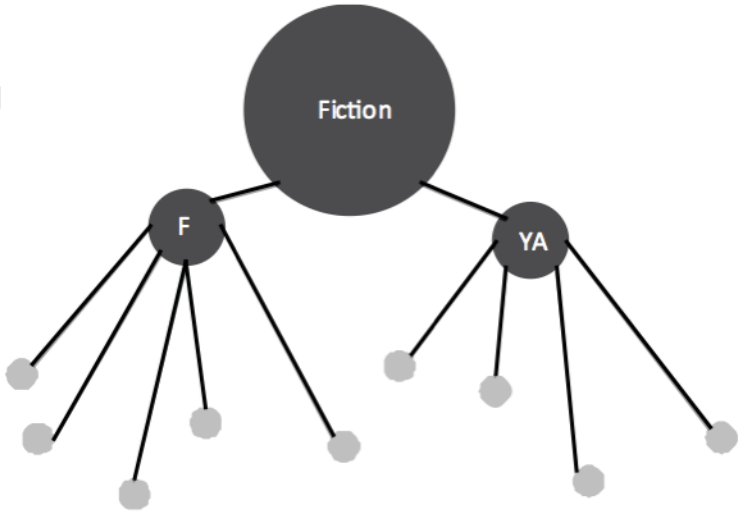


Read Vector to Cluster mappings

Other clustering algorithms



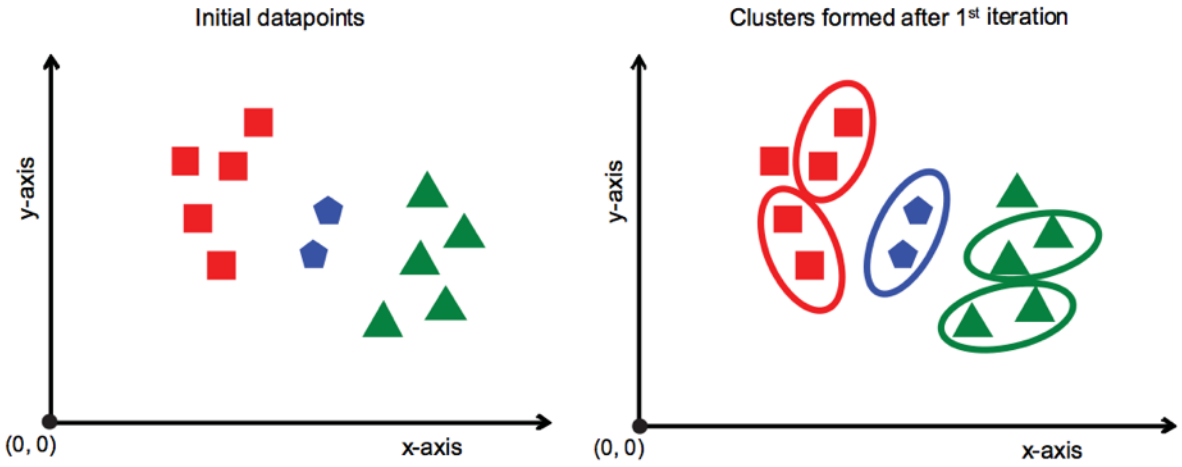
Hierarchical clustering



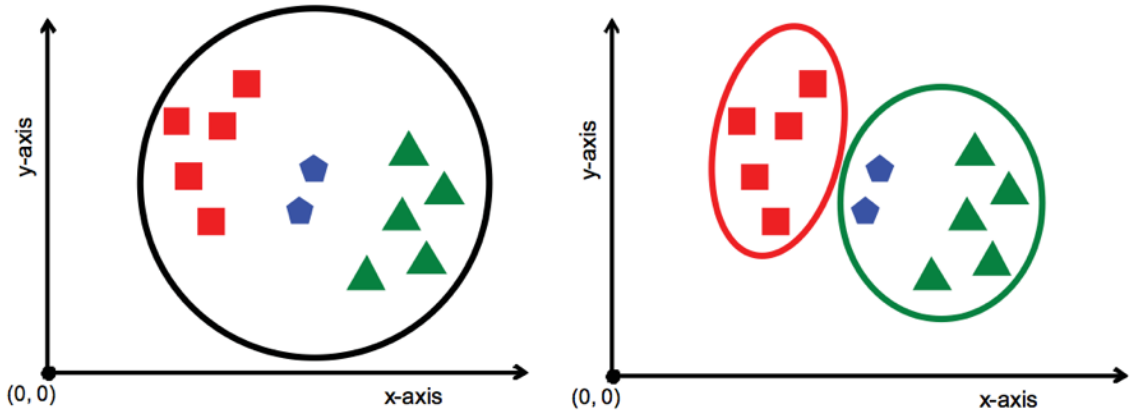
Different clustering approaches

FIXED NUMBER OF CENTERS

BOTTOM-UP APPROACH: FROM POINTS TO CLUSTERS VIA GROUPING



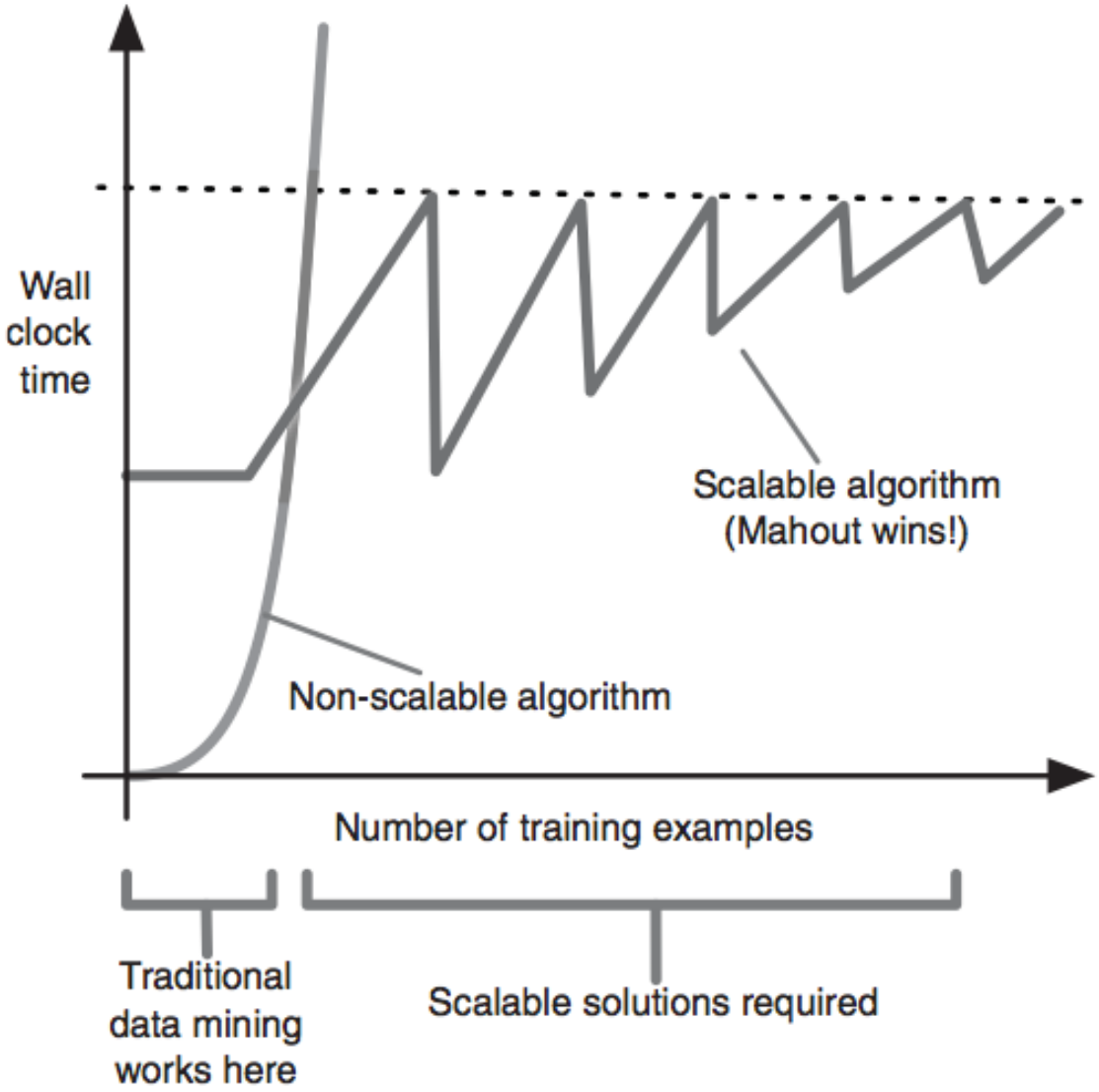
TOP-DOWN APPROACH: SPLITTING THE GIANT CLUSTER



When to use Mahout for classification?

System size in number of examples	Choice of classification approach
< 100,000	Traditional, non-Mahout approaches should work very well. Mahout may even be slower for training.
100,000 to 1 million	Mahout begins to be a good choice. The flexible API may make Mahout a preferred choice, even though there is no performance advantage.
1 million to 10 million	Mahout is an excellent choice in this range.
> 10 million	Mahout excels where others fail.

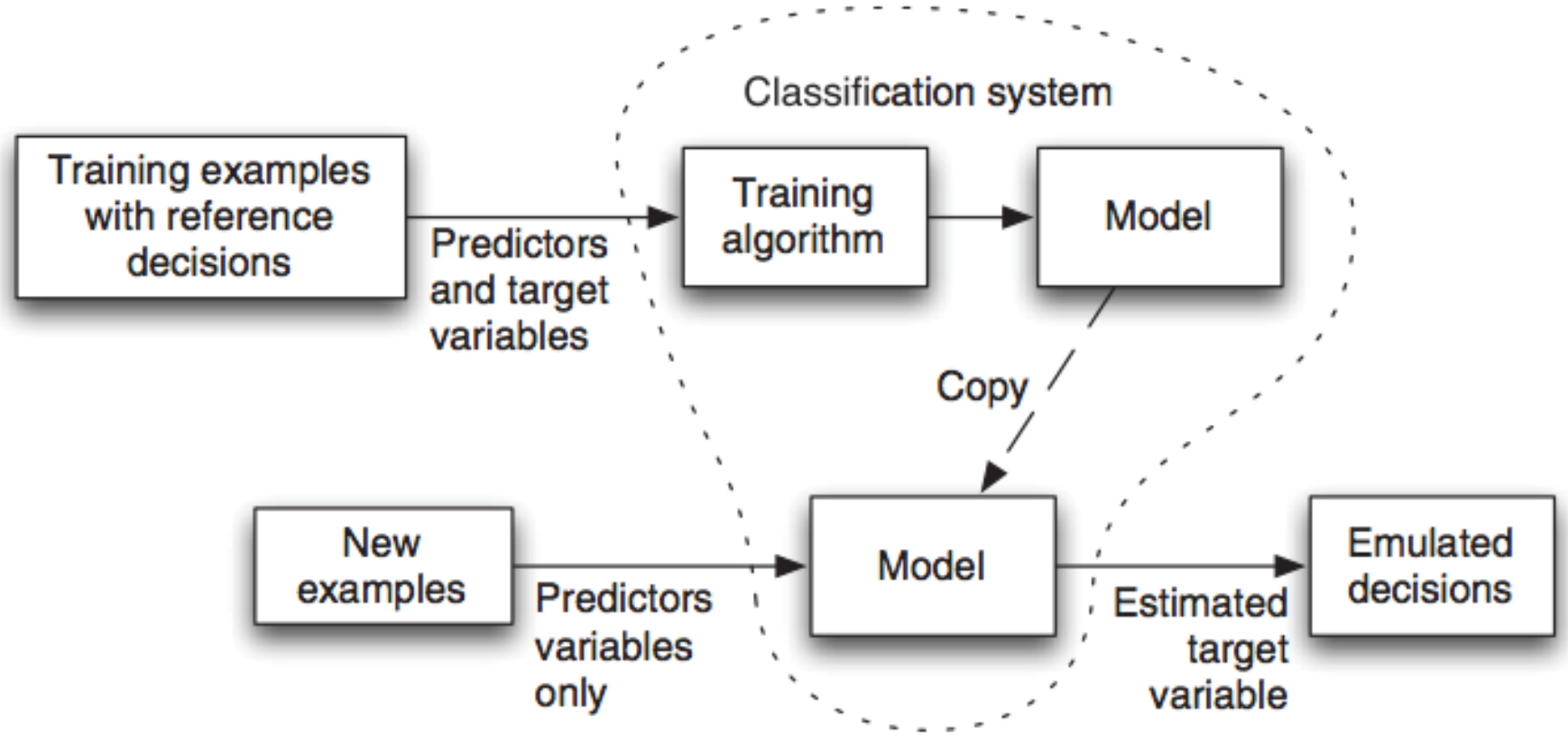
The advantage of using Mahout for classification



Classification — definition

DEFINITION Computer classification systems are a form of machine learning that use learning algorithms to provide a way for computers to make decisions based on experience and, in the process, emulate certain forms of human decision making.

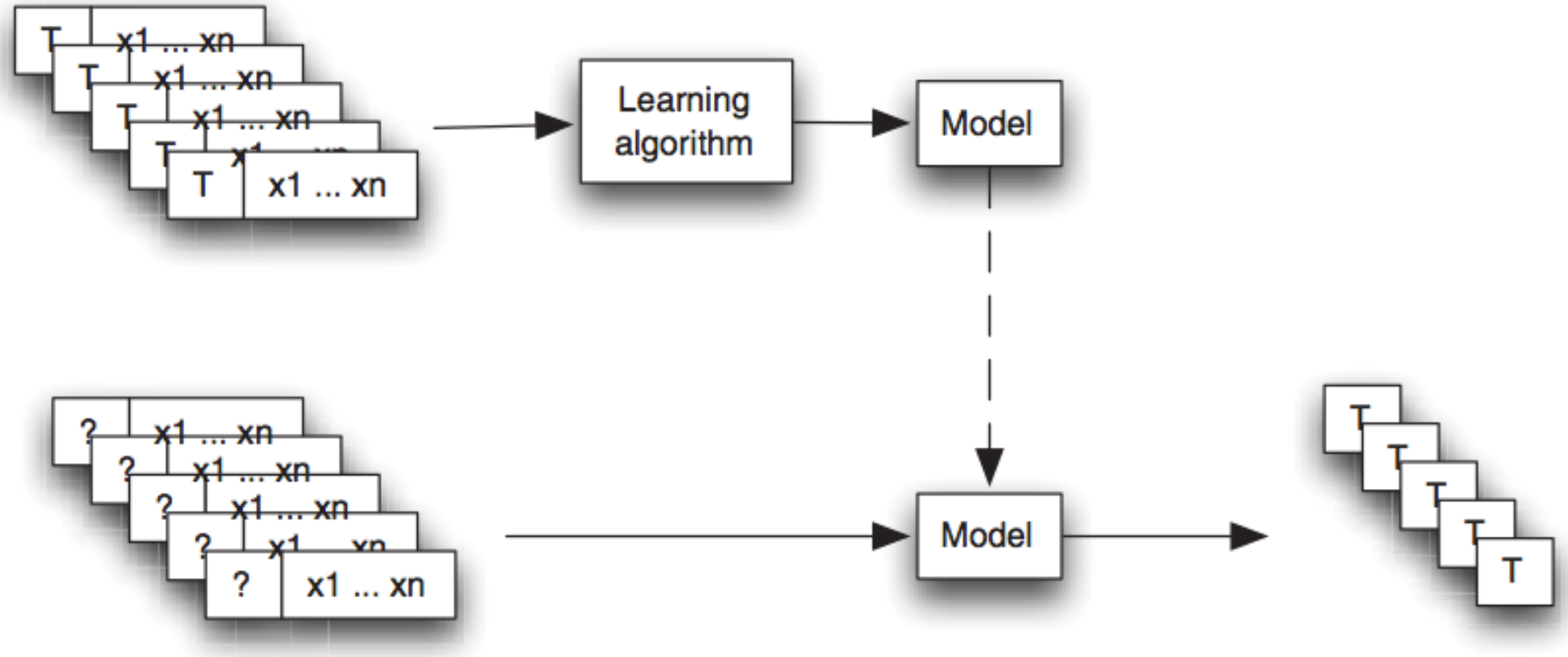
How does a classification system work?



Key terminology for classification

Key Idea	Description
Model	A computer program that makes decisions; in classification, the output of the training algorithm is a model.
Training data	A subset of training examples labeled with the value of the target variable and used as input to the learning algorithm to produce the model.
Test data	A withheld portion of the training data with the value of the target variable hidden so that it can be used to evaluate the model.
Training	The learning process that uses training data to produce a model. That model can then compute estimates of the target variable given the predictor variables as inputs.
Training example	An entity with features that will be used as input for learning algorithm.
Feature	A known characteristic of a training or a new example; a feature is equivalent to a characteristic.
Variable	In this context, the value of a feature or a function of several features. This usage is somewhat different from the use of *variable* in a computer program.
Record	A container where an example is stored; such a record is composed of fields.
Field	Part of a record that contains the value of a feature (a variable).
Predictor variable	A feature selected for use as input to a classification model. Not all features need be used. Some features may be algorithmic combinations of other features.
Target variable	A feature that the classification model is attempting to estimate: the target variable is categorical, and its determination is the aim of the classification system.

Input and Output of a classification model



Four types of values for predictor variables

Type of value	Description
Continuous	This is a floating-point value. This type of value might be a price, a weight, a time, or anything else that has a numerical magnitude and where this magnitude is the key property of the value.
Categorical	A categorical value can have one of a set of prespecified values. Typically the set of categorical values is relatively small and may be as small as two, although the set can be quite large. Boolean values are generally treated as categorical values. Another example might be a vendor ID.
Word-like	A word-like value is like a categorical value, but it has an open-ended set of possible values.
Text-like	A text-like value is a sequence of word-like values, all of the same kind. Text is the classic example of a text-like value, but a list of email addresses or URLs is also text-like.

Sample data that illustrates all four value types

Name	Type	Value
from-address	Word-like	`George <george@fumble-tech.com>`
in-address-book?	Categorical (`TRUE`, `FALSE`)	`TRUE`
non-spam-words	Text-like	`Ted, Mahout, User, lunch`
spam-words	Text-like	`available`
unknown-words	Continuous	`0`
message-length	Continuous	`31`

Supervised vs. Unsupervised Learning

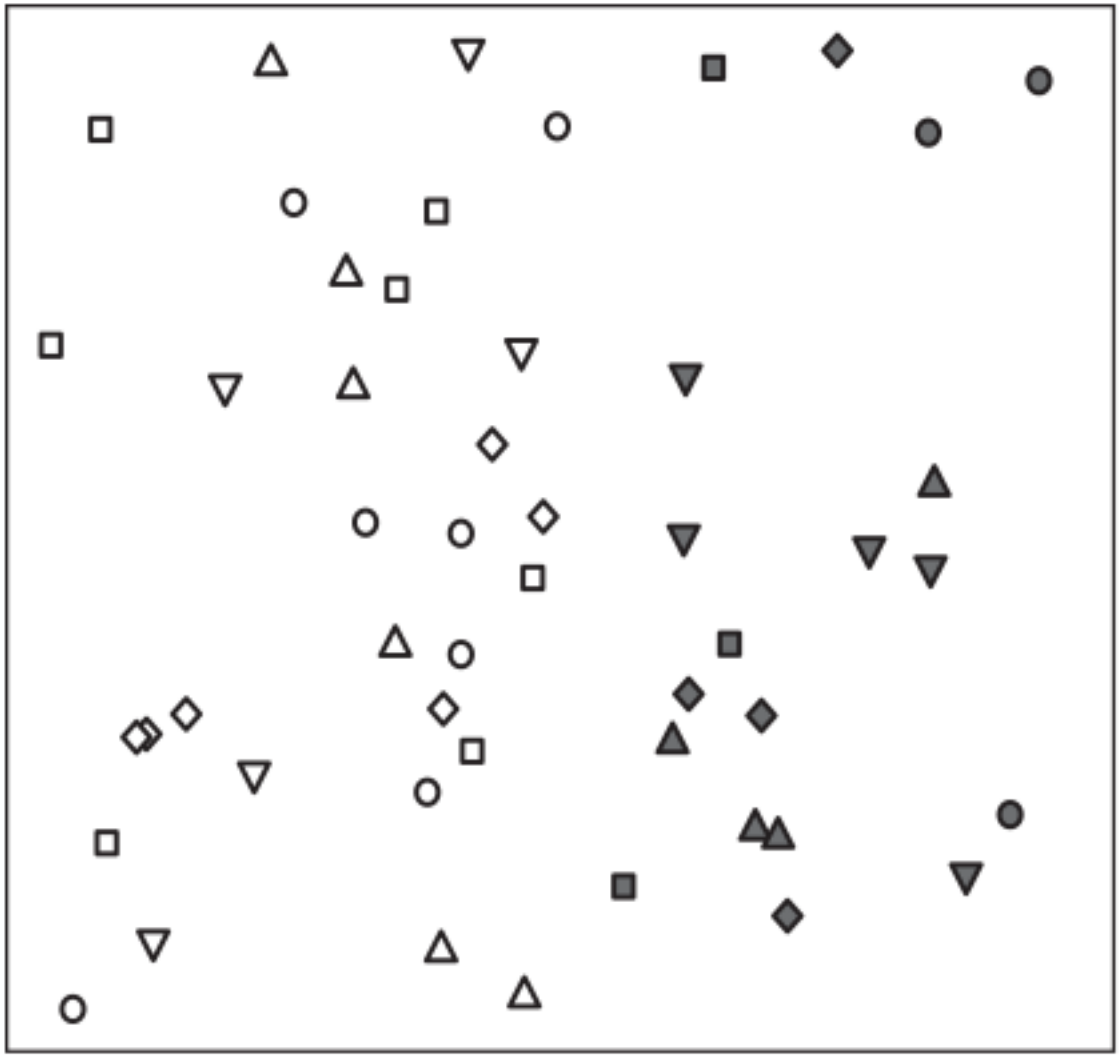
Classification algorithms are related to, but still quite different from, clustering algorithms such as the k-means algorithm described in previous chapters. Classification algorithms are a form of supervised learning, as opposed to unsupervised learning, which happens with clustering algorithms. A supervised learning algorithm is one that's given examples that contain the desired value of a target variable. Unsupervised algorithms aren't given the desired answer, but instead must find something plausible on their own.

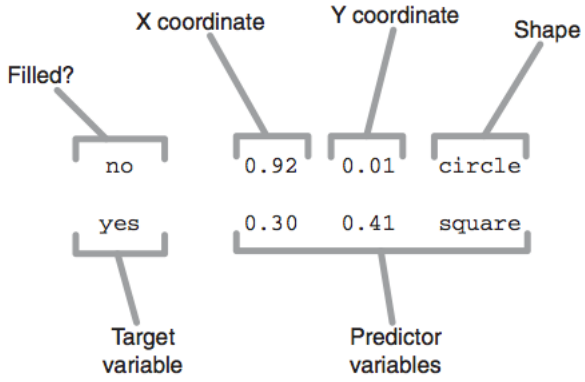
Supervised and unsupervised learning algorithms can often be usefully combined. A clustering algorithm can be used to create features that can then be used by a learning algorithm, or the output of several classifiers can be used as features by a clustering algorithm. Moreover, clustering systems often build a model that can be used to categorize new data. This clustering system model works much like the model produced by a classification system. The difference lies in what data was used to produce the model. For classification, the training data includes the target variables; for clustering, the training data doesn't include target variables.

Work flow in a typical classification project

Stage	Step
1. Training the model	Define target variable. Collect historical data. Define predictor variables. Select a learning algorithm. Use the learning algorithm to train the model.
2. Evaluating the model	Run test data. Adjust the input (use different predictor variables, different algorithms, or both).
3. Using the model in production	Input new examples to estimate unknown target values. Retrain the model as needed.

Classification Example 1 — Color-Fill



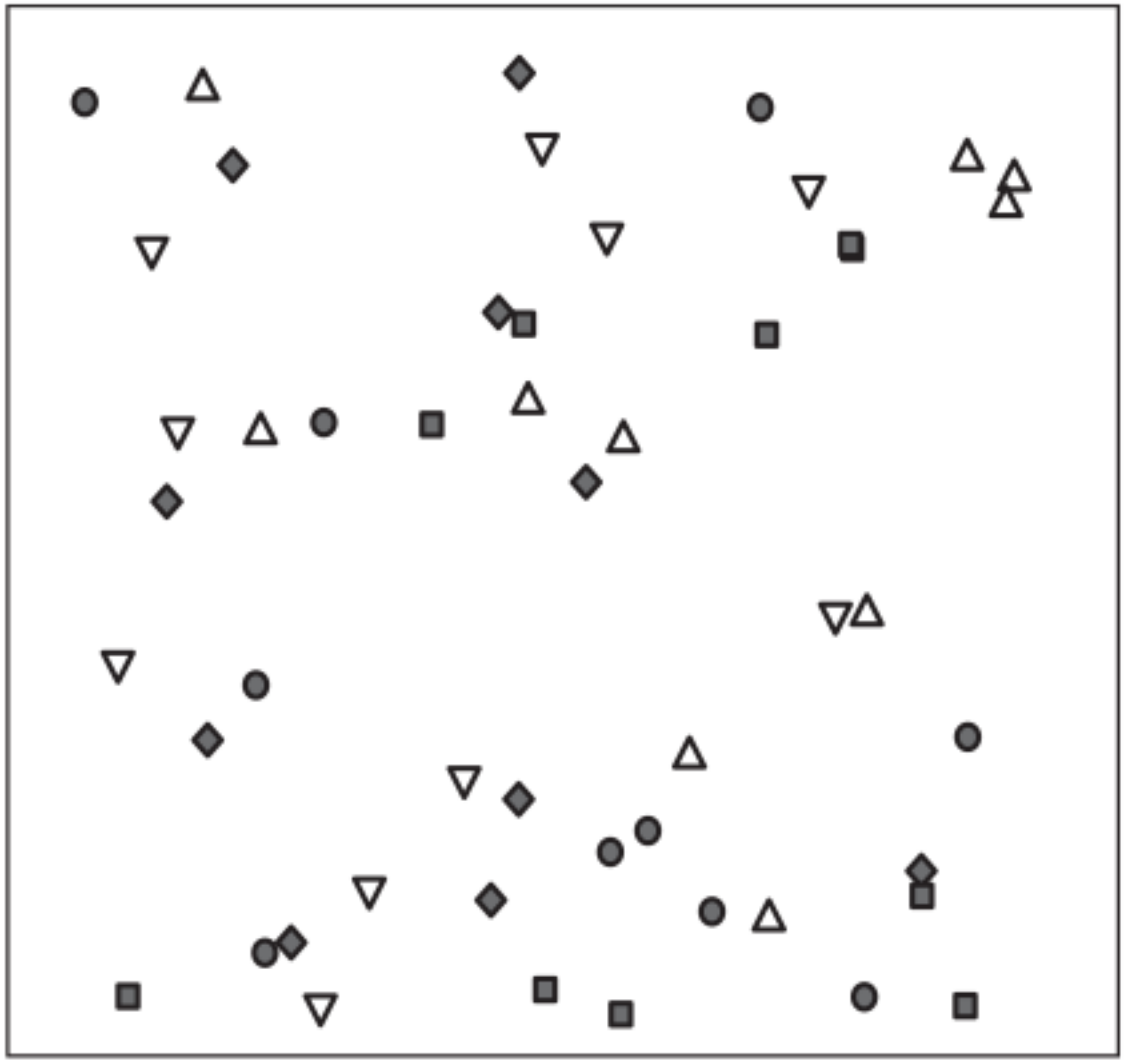


Position looks promising, especially the x-axis ==> predictor variable.
Shape seems to be irrelevant. Target variable is “color-fill” label.

Target leak

- A target leak is a bug that involves unintentionally providing data about the target variable in the section of the predictor variables.
- Don't confused with intentionally including the target variable in the record of a training example.
- Target leaks can seriously affect the accuracy of the classification system.

Classification Example 2 — Color-Fill (another feature)

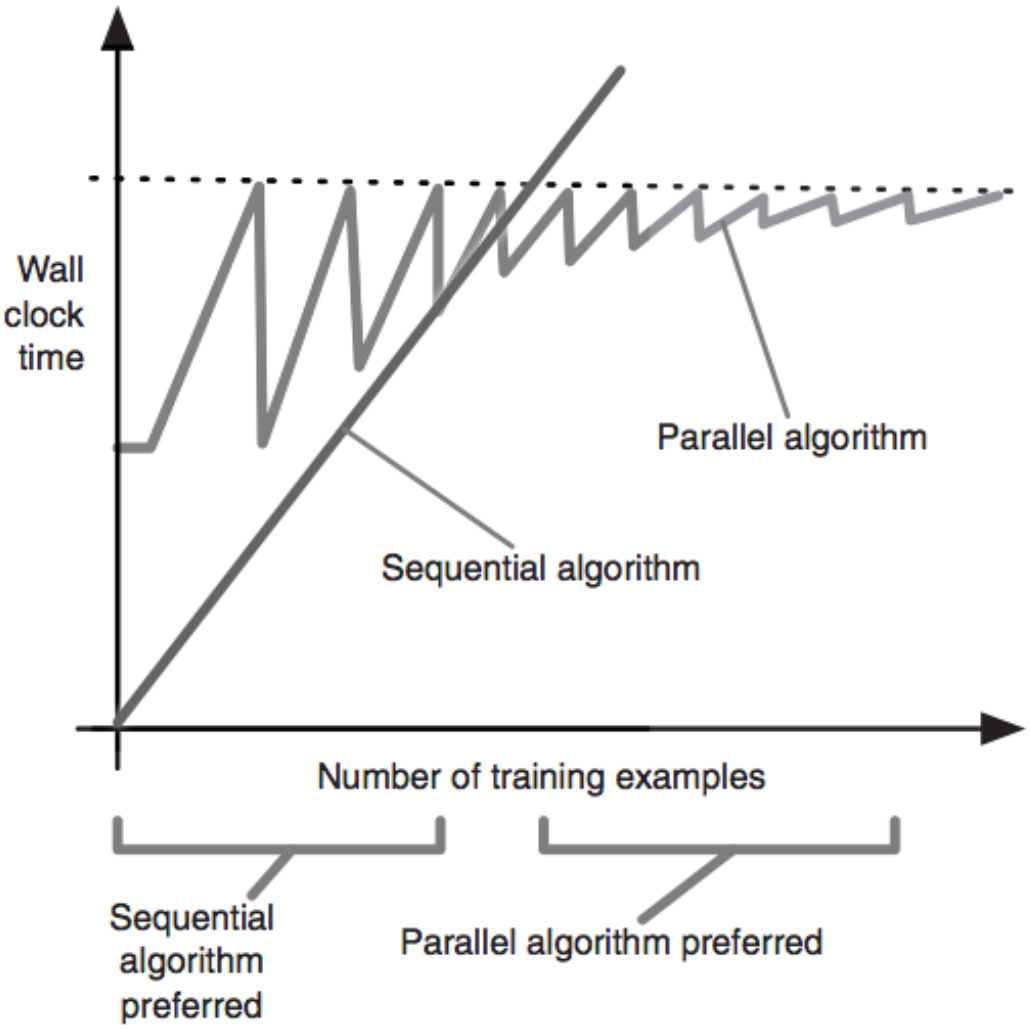


Mahout classification algorithms

Mahout classification algorithms include:

- Naive Bayesian
- Complementary Naive Bayesian
- Stochastic Gradient Descent (SDG)
- Random Forest

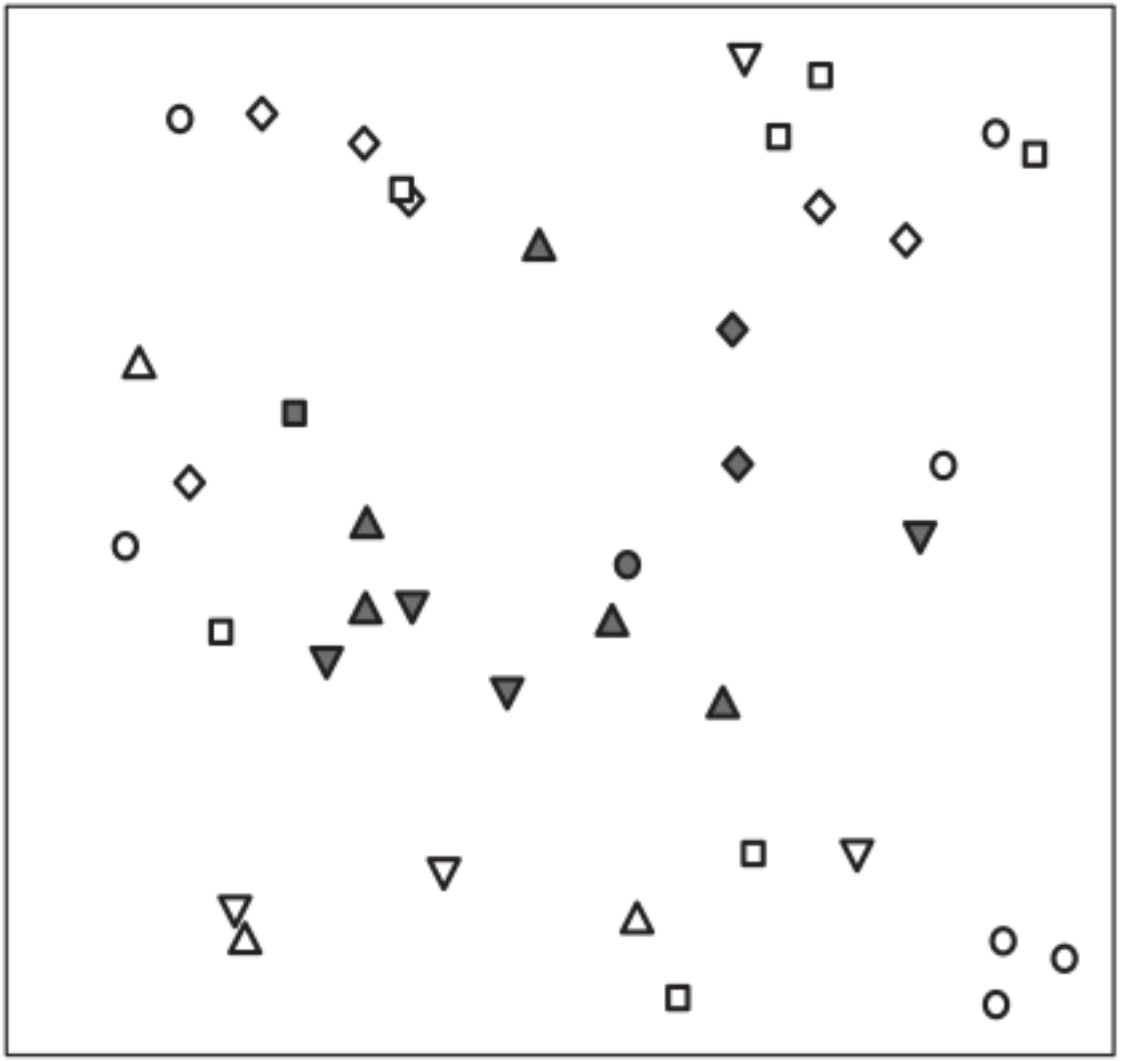
Comparing two types of Mahout Scalable algorithms



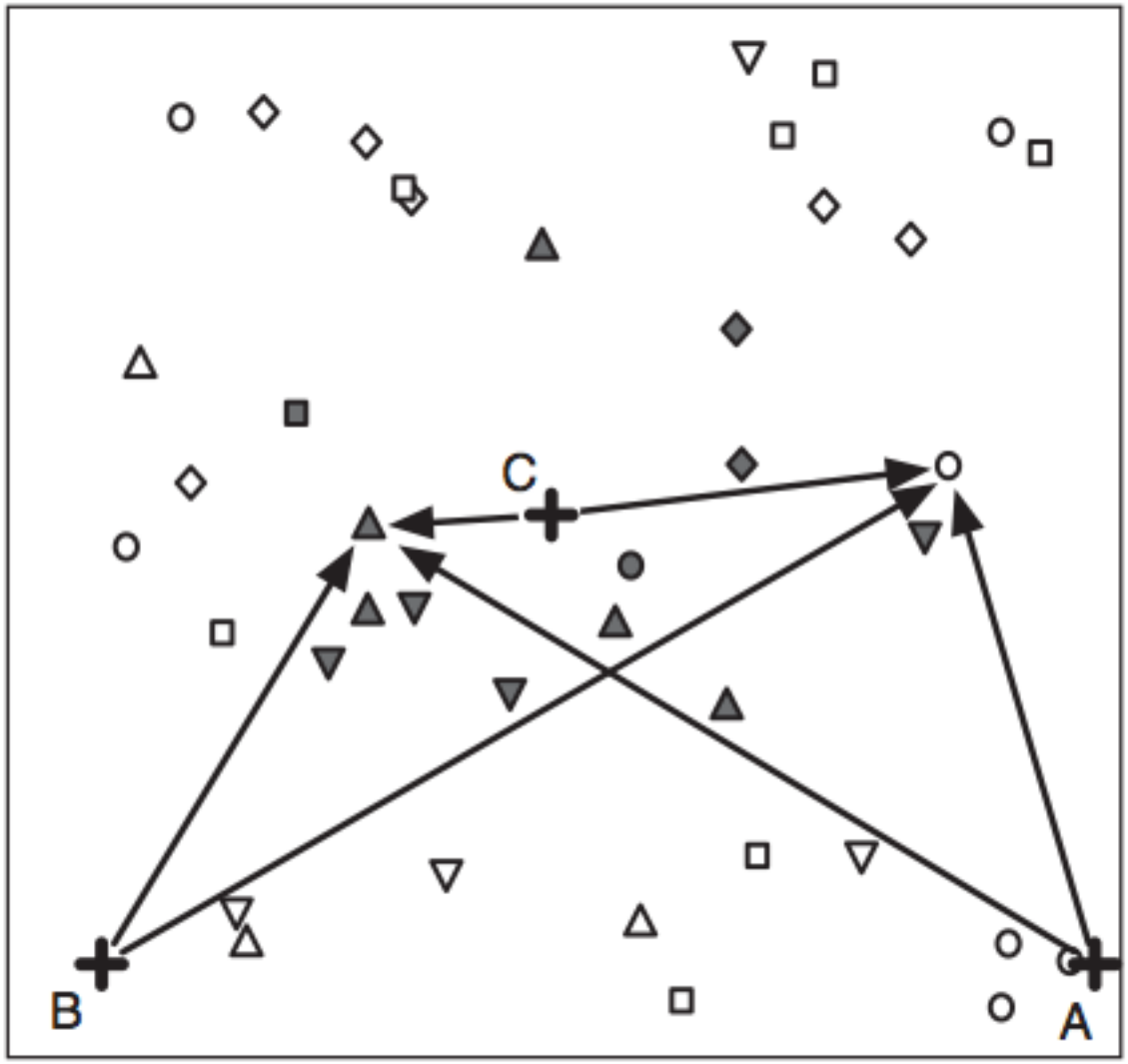
Step-by-step simple classification example

1. The data and the challenge
2. Training a model to find color-fill: preliminary thinking
3. Choosing a learning algorithm to train the model
4. Improving performance of the classifier

Classification Example 3



What may be a good predictor?



Choose algorithm via Mahout

Size of data set	Mahout algorithm	Execution model	Characteristics
Small to medium (less than tens of millions of training examples)	Stochastic gradient descent (SGD) family: `OnlineLogisticRegression`, `CrossFoldLearner`, `AdaptiveLogisticRegression`	Sequential, online, incremental	Uses all types of predictor variables; sleek and efficient over the appropriate data range (up to millions of training examples)
	Support vector machine (SVM)	Sequential	Experimental still; sleek and efficient over the appropriate data range
Medium to large (millions to hundreds of millions of training examples)	Naive Bayes	Parallel	Strongly prefers text-like data; medium to high overhead for training; effective and useful for data sets too large for SGD or SVM
	Complementary naive Bayes	Parallel	Somewhat more expensive to train than naive Bayes; effective and useful for data sets too large for SGD, but has similar limitations to naive Bayes
Small to medium (less than tens of millions of training examples)	Random forests	Parallel	Uses all types of predictor variables; high overhead for training; not widely used (yet); costly but offers complex and interesting classifications, handles nonlinear and conditional relationships in data better than other techniques

Stochastic Gradient Descent (SGD)

Both statistical estimation and machine learning consider the problem of minimizing an objective function that has the form of a sum:

$$Q(w) = \sum_{i=1}^{n} Q_i(w),$$

where the parameter w is to be estimated and where typically each summand function $Q_i()$ is associated with the i-th observation in the data set (used for training).

- Choose an initial vector of parameters w and learning rate α.
- Randomly shuffle examples in the training set.
- Repeat until an approximate minimum is obtained:
  - For $i = 1, 2, ..., n$, do:
    - $w := w - \alpha \nabla Q_i(w)$.

Let's suppose we want to fit a straight line $y = w_1 + w_2 x$ to a training set of two-dimensional points $(x_1, y_1), \ldots, (x_n, y_n)$ using least squares. The objective function to be minimized is:

$$Q(w) = \sum_{i=1}^{n} Q_i(w) = \sum_{i=1}^{n} (w_1 + w_2 x_i - y_i)^2 .$$

The last line in the above pseudocode for this specific problem will become:

$$\begin{bmatrix} w_1 \\ w_2 \end{bmatrix} := \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} - \alpha \begin{bmatrix} \sum_{i=1}^{n} 2(w_1 + w_2 x_i - y_i) \\ \sum_{i=1}^{n} 2x_i(w_1 + w_2 x_i - y_i) \end{bmatrix}.$$

Characteristic of SGD

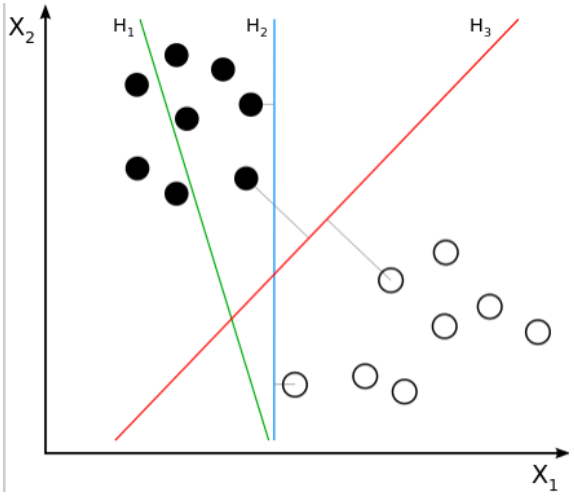
Columbia University

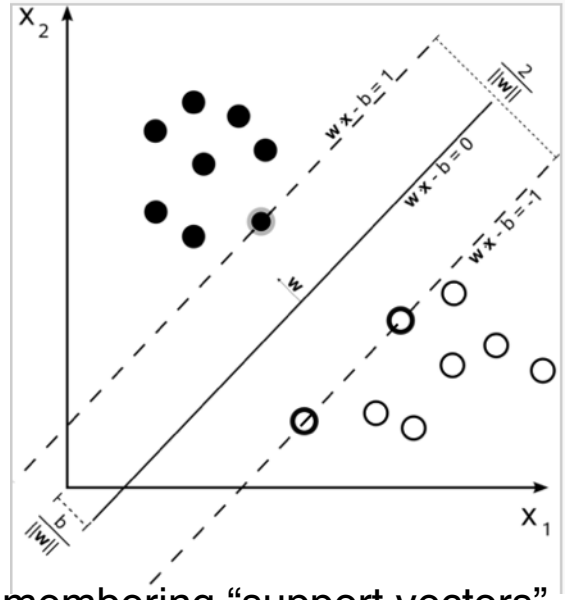
THE SGD ALGORITHM

Stochastic gradient descent (SGD) is a widely used learning algorithm in which each training example is used to tweak the model slightly to give a more correct answer for that one example. This incremental approach is repeated over many training examples. With some special tricks to decide how much to nudge the model, the model accurately classifies new data after seeing only a modest number of examples. Although SGD algorithms are difficult to parallelize effectively, they're often so fast that for a wide variety of applications, parallel execution isn't necessary.

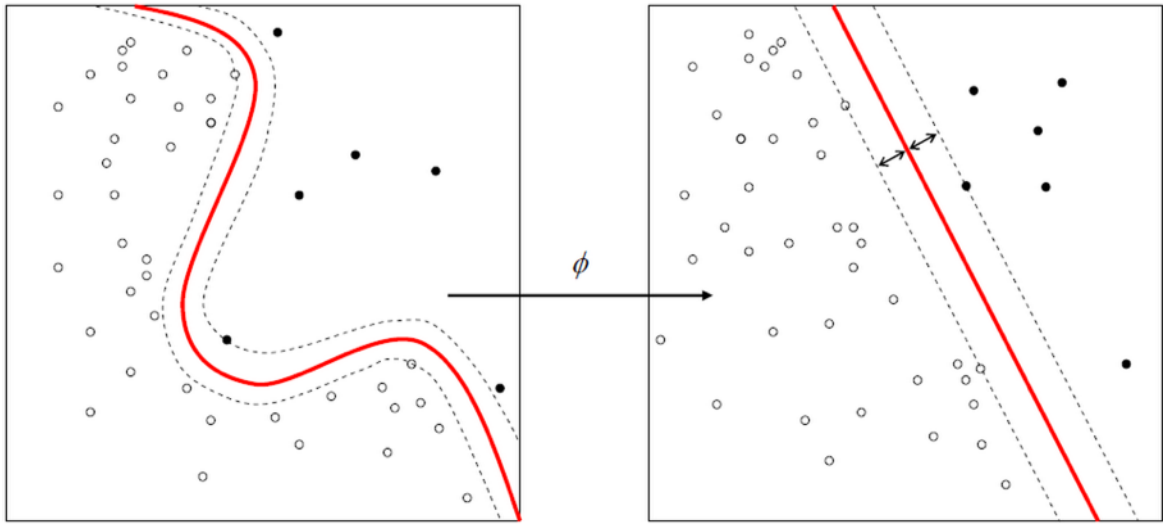
Importantly, because these algorithms do the same simple operation for each training example, they require a constant amount of memory. For this reason, each training example requires roughly the same amount of work. These properties make SGD-based algorithms scalable in the sense that twice as much data takes only twice as long to process.

Support Vector Machine (SVM)





maximize boundary distances; remembering “support vectors”



nonlinear kernels

Naive Bayes

Training set:

sex	height (feet)	weight (lbs)	foot size(inches)
male	6	180	12
male	5.92 (5'11")	190	11
male	5.58 (5'7")	170	12
male	5.92 (5'11")	165	10
female	5	100	6
female	5.5 (5'6")	150	8
female	5.42 (5'5")	130	7
female	5.75 (5'9")	150	9

Classifier using Gaussian distribution assumptions:

sex	mean (height)	variance (height)	mean (weight)	variance (weight)	mean (foot size)	variance (foot size)
male	5.855	3.5033e-02	176.25	1.2292e+02	11.25	9.1667e-01
female	5.4175	9.7225e-02	132.5	5.5833e+02	7.5	1.6667e+00

$$posterior(male) = \frac{P(male)\,p(height|male)\,p(weight|male)\,p(footsize|male)}{evidence}$$

Test Set:

sex	height (feet)	weight (lbs)	foot size(inches)
sample	6	130	8

$$evidence = P(male)\,p(height|male)\,p(weight|male)\,p(footsize|male) + P(female)\,p(height|female)\,p(weight|female)\,p(footsize|female)$$

$$P(male) = 0.5$$

$$p(\text{height}|\text{male}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-(6-\mu)^2}{2\sigma^2}\right) \approx 1.5789,$$

$$p(\text{weight}|\text{male}) = 5.9881 \cdot 10^{-6}$$
$$p(\text{foot size}|\text{male}) = 1.3112 \cdot 10^{-3}$$
$$\text{posterior numerator (male)} = \text{their product} = 6.1984 \cdot 10^{-9}$$

$$P(\text{female}) = 0.5$$
$$p(\text{height}|\text{female}) = 2.2346 \cdot 10^{-1}$$
$$p(\text{weight}|\text{female}) = 1.6789 \cdot 10^{-2}$$
$$p(\text{foot size}|\text{female}) = 2.8669 \cdot 10^{-1}$$
$$\text{posterior numerator (female)} = \text{their product} = 5.3778 \cdot 10^{-4}$$

==> female

Random Forest

Random forests are an ensemble learning method for classification (and regression) that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes output by individual trees.

The training algorithm for random forests applies the general technique of bootstrap aggregating, or bagging, to tree learners. Given a training set $X = x_1, \ldots, x_n$ with responses $Y = y_1$ through y_n, bagging repeatedly selects a bootstrap sample of the training set and fits trees to these samples:

For b = 1 through B:

1. Sample, with replacement, n training examples from X, Y; call these X_b, Y_b.
2. Train a decision or regression tree f_b on X_b, Y_b.

After training, predictions for unseen samples x' can be made by averaging the predictions from all the individual regression trees on x':

$$\hat{f} = \frac{1}{B}\sum_{b=1}^{B} \hat{f}_b(x')$$

or by taking the majority vote in the case of decision trees.

Random forest uses a modified tree learning algorithm that selects, at each candidate split in the learning process, a random subset of the features.

Choosing a learning algorithm to train the model

- One low overhead classification method is the stochastic gradient descent (SGD) algorithm for logistic regression.
- This algorithm is sequential, but it's fast.

START RUNNING MAHOUT

```
$ $MAHOUT_HOME/bin/mahout
An example program must be given as the first argument.
Valid program names are:
  canopy: : Canopy clustering
  cat : Print a file or resource as the logistic regression models would see
     it
...
  runlogistic : Run a logistic regression model against CSV data
  ...
 trainlogistic : Train a logistic regression using stochastic gradient
     descent
 ...
```

CHECK MAHOUT'S BUILT-IN DATA

```
$ bin/mahout cat donut.csv
"x","y","shape","color","k","k0","xx","xy","yy","a","b","c","bias"
0.923307513352484,0.0135197141207755,21,2,4,8,0.852496764213146,...,1
0.711011884035543,0.909141522599384,22,2,3,9,0.505537899239772,...,1
...
0.67132937326096,0.571220482233912,23,1,5,2,0.450683127402953,...,1
0.548616112209857,0.405350996181369,24,1,5,3,0.300979638576258,...,1
0.677980388281867,0.993355110753328,25,2,3,9,0.459657406894831,...,1
$
```

The donut.csv data file in Example 3

Variable	Description	Possible values
x	The *x* coordinate of a point	Numerical from 0 to 1
y	The *y* coordinate of a point	Numerical from 0 to 1
shape	The shape of a point	Shape code from 21 to 25
color	Whether the point is filled or not	1=empty, 2=filled
k	The k-means cluster ID derived using only *x* and *y*	Integer cluster code from 1 to 10
k0	The k-means cluster ID derived using *x*, *y*, and color	Integer cluster code from 1 to 10
xx	The square of the *x* coordinate	Numerical from 0 to 1
xy	The product of the *x* and *y* coordinates	Numerical from 0 to 1
yy	The square of the *y* coordinate	Numerical from 0 to 1
a	The distance from the point (0,0)	Numerical from 0 to $\sqrt{2}$
b	The distance from the point (1,0)	Numerical from 0 to $\sqrt{2}$
c	The distance from the point (0.5,0.5)	Numerical from 0 to $(\sqrt{2})/2$
bias	A constant	1

Build a model using Mahout

```
$ bin/mahout trainlogistic --input donut.csv \
        --output ./model \
        --target color --categories 2 \
        --predictors x y  --types numeric \
        --features 20 --passes 100 --rate 50
...
color ~ -0.157*Intercept Term + -0.678*x + -0.416*y
      Intercept Term -0.15655
                   x -0.67841
                   y -0.41587
...
```

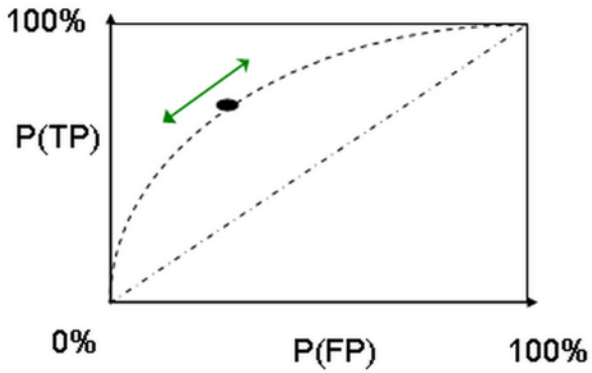
This command specifies that the input comes from the resource named donut.csv, that the resulting model is stored in the file ./model, that the target variable is in the field named `color` and that it has two possible values. The command also specifies that the algorithm should use variables `x` and `y` as predictors, both with numerical types. The remaining options specify internal parameters for the learning algorithm.

Trainlogistic program

Option	What it does
`--quiet`	Produces less status and progress output.
`--input <file-or-resource>`	Uses the specified file or resource as input.
`--output <file-for-model>`	Puts the model into the specified file.
`--target <variable>`	Uses the specified variable as the target.
`--categories <n>`	Specifies how many categories the target variable has.
`--predictors <v1> ... <vn>`	Specifies the names of the predictor variables.
`--types <t1> ... <tm>`	Gives a list of the types of the predictor variables. Each type should be one of `numeric`, `word`, or `text`. Types can be abbreviated to their first letter. If too few types are given, the last one is used again as necessary. Use `word` for categorical variables.
`--passes`	Specifies the number of times the input data should be reexamined during training. Small input files may need to be examined dozens of times. Very large input files probably don't even need to be completely examined.
`--lambda`	Controls how much the algorithm tries to eliminate variables from the final model. A value of 0 indicates no effort is made. Typical values are on the order of 0.00001 or less.
`--rate`	Sets the initial learning rate. This can be large if you have lots of data or use lots of passes because it's decreased progressively as data is examined.
`--noBias`	Eliminates the intercept term (a built-in constant predictor variable) from the model. Occasionally this is a good idea, but generally it isn't since the SGD learning algorithm can usually eliminate the intercept term if warranted.
`--features`	Sets the size of the internal feature vector to use in building the model. A larger value here can be helpful, especially with text-like input data.

Evaluate the model

```
$  bin/mahout runlogistic --input donut.csv --model ./model \
        --auc --confusion
AUC = 0.57
confusion: [[27.0, 13.0], [0.0, 0.0]]
...
```



AUC (0 ~ 1):
- 1 — perfect
- 0 — perfectly wrong
- 0.5 — random

True positive	**False positive** (Type I error)
False negative (Type II error)	**True negative**

confusion matrix

Option	What it does
`--quiet`	Produces less status and progress output.
`--auc`	Prints AUC score for model versus input data after reading data.
`--scores`	Prints target variable value and scores for each input example.
`--confusion`	Prints confusion matrix for a particular threshold (see `--threshold`).
`--input <input>`	Reads data records from specified file or resource.
`--model <model>`	Reads model from specified file.

Questions?