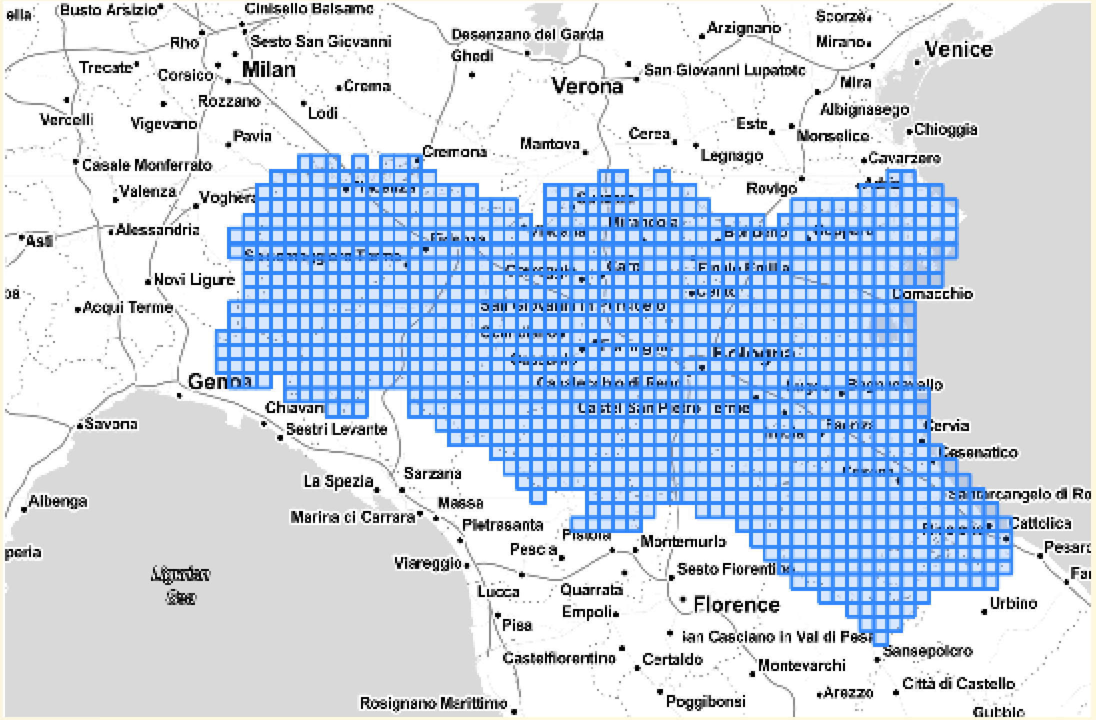
Big Data Analytics Project

ARPAE Climate Time-Series Clustering



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Project Description

- **Time Series Clustering** on Temperature (min/max) and Preciptitation Data taken from ARPAE (Emilia Romagna).
- The region has been divided in **1131 areas**, each having 3 daily 63 years long time series of the aforementioned data.
- For memory reasons we only used a span of **3 years** (1970~1972) extracting 3 datasets of size:

```
Dataframe Size: (1131, 1097),  Total Entries: 1240707
```

HADOOP SETUP

- HDFS runs on 3 Machines:
  - 1 Namenode (Node Master)
  - 2 Datanodes (Node1 and Node2)
- YARN as a resource Manager which is used as a **Spark Master**.

SPARK SETUP

```
import findspark

findspark.init()

import pyspark
from pyspark.sql import SparkSession

spark = SparkSession \
            .builder \
            .appName("BDAProject") \
            .config("spark.executor.memory","1100m")\
            .config("spark.executor.memoryOverhead","400m")\
            .master("yarn") \
            .getOrCreate()
```

SPARK SETUP

- Each dataset (TMAX, TMIN, PREC) is then loaded for separate analysis using the SparkSession **read** method and managed as a **Spark DataFrame**.
- The **DataFrame** is then processed and used as an input for Clustering Algorithms.

DATASET SCHEMA

- The Timeseries have been transformed into sime-spanned records using the following *Pyspark schema*.

```
from pyspark.sql.types import StructType, StructField, DoubleType, StringType

suff_list = ["1970_d.csv","1971_d.csv","1972_d.csv"]

dates = []
for suff in suff_list:
    df = pd.read_csv(path+f"00019_{suff}")
    for i in range(len(df['PragaDate'])):
        dates.append(df['PragaDate'][i])

schema = StructType([StructField("AREA", StringType(), True)]+[ StructField(date, DoubleType(), True) for date in dates])
```

Clustering Pipeline

Clustering Pipeline - 1

Dataset Loading

```
sparkDF = spark.read.schema(schema).json(f"DAILY_{feature}_dataset.json")
```

Vector Assembler on Features (Timespan Columns)

```
vecAssembler = VectorAssembler(outputCol="features")
vecAssembler.setInputCols(column_names)
sparkDF = vecAssembler.transform(sparkDF)
```

Features Scaler

```
scaler = StandardScaler(inputCol = 'features', outputCol = 'scaledFeatures', withMean = True,
withStd = True).fit(sparkDF)
```

Clustering Pipeline - 2

PCA on Features extracting 2 components

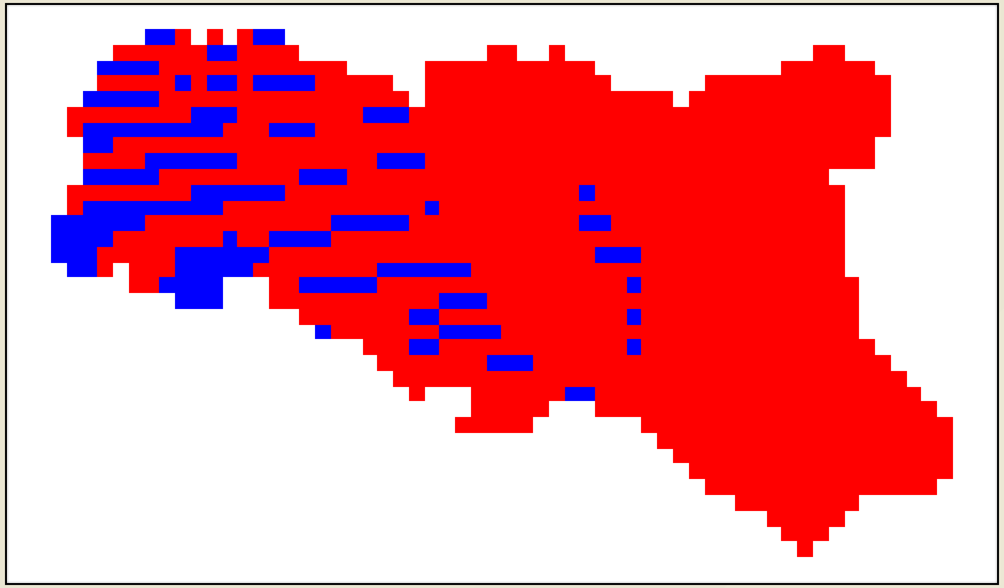
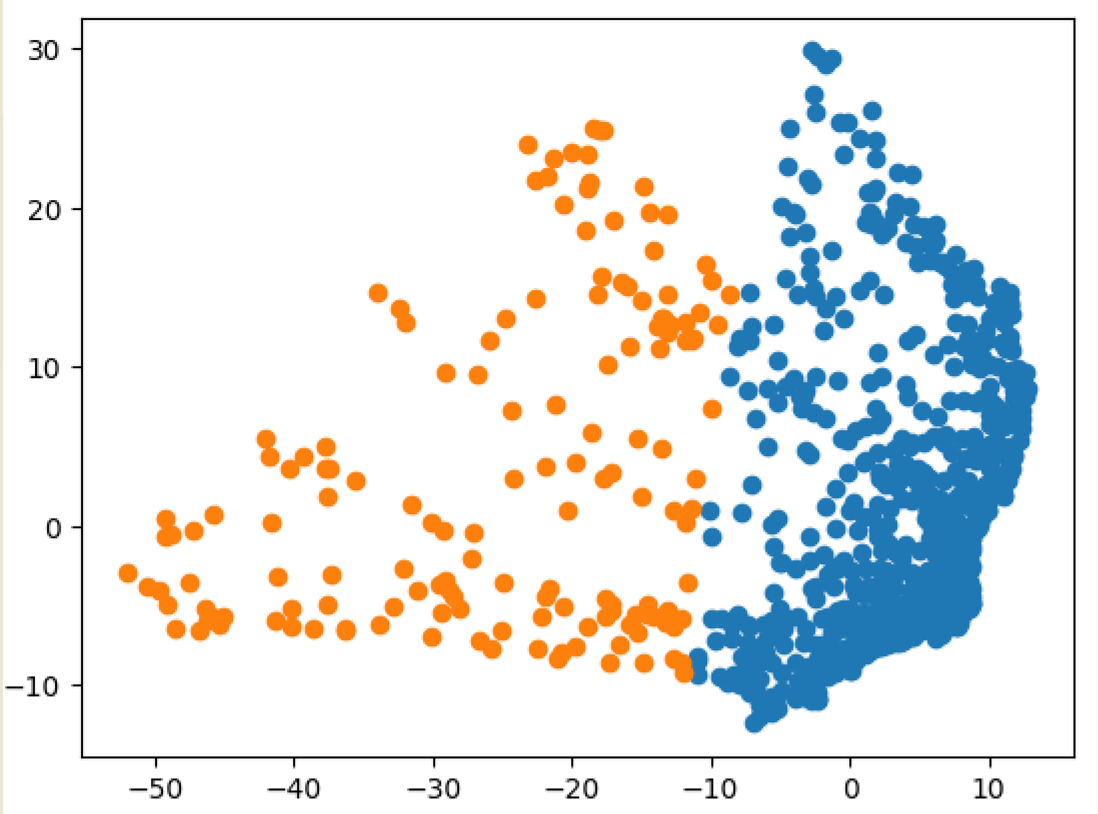
```
pca = PCA(k = n_components_pca, inputCol = 'scaledFeatures',
        outputCol = 'pcaFeatures').fit(sparkDF)
```

Running Clustering Algorithm (KMeans, Bisecting KMeans, GMM)

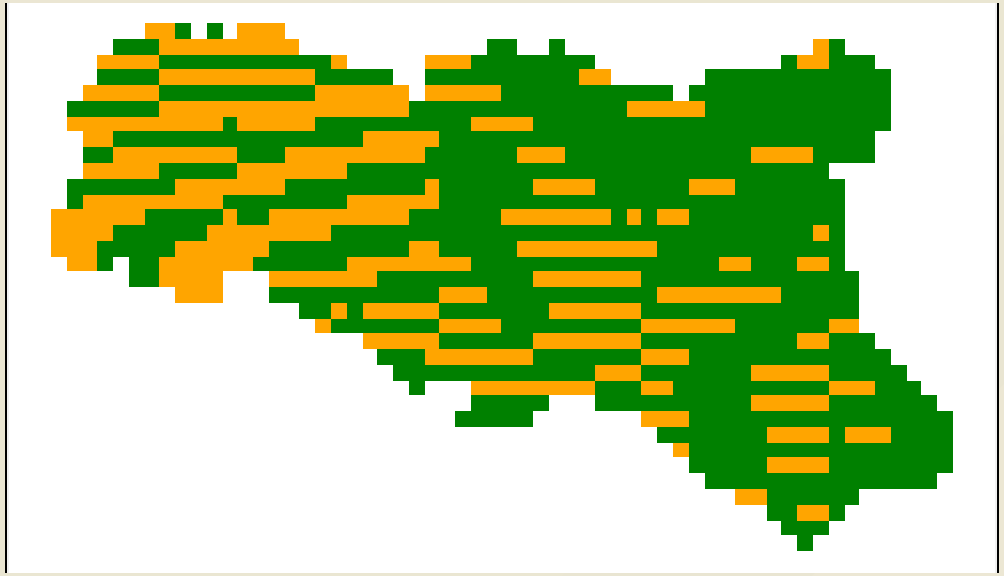
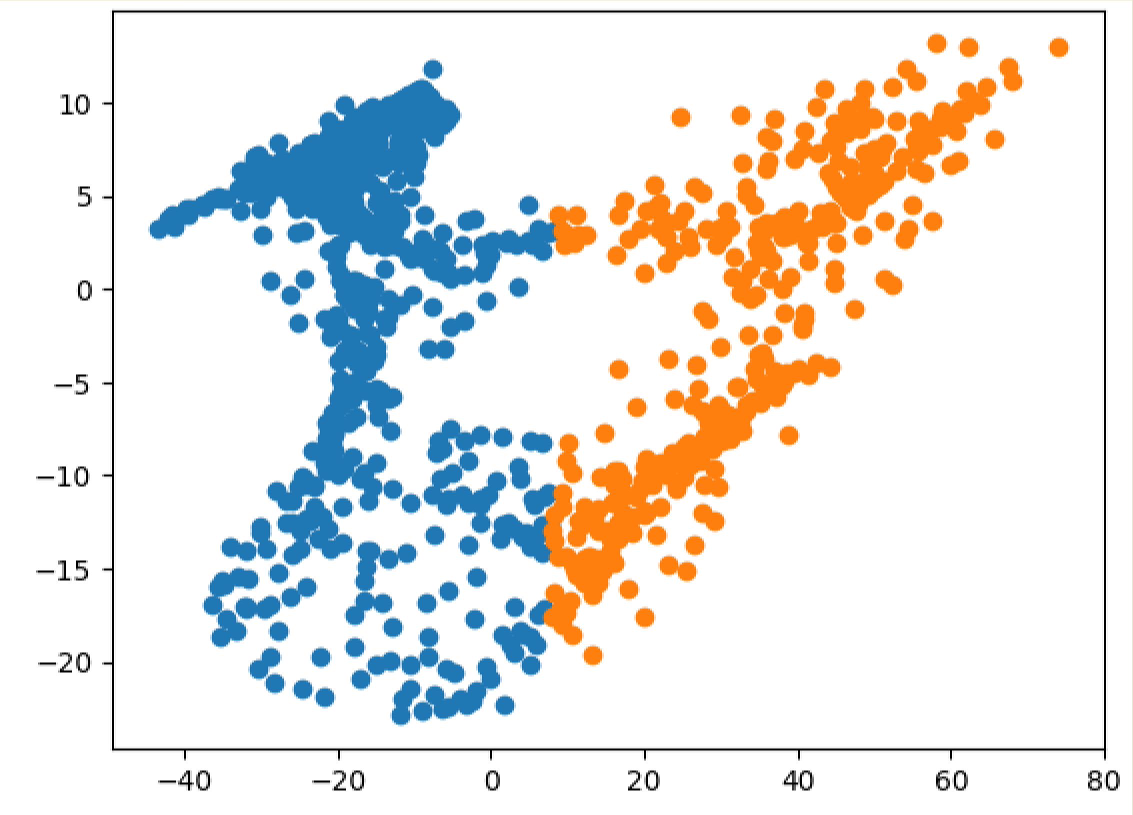
```
cmethod = clustering_function(featuresCol="pcaFeatures").setK(cluster_number).setSeed(1)
model = cmethod.fit(sparkDF)
predictions = model.transform(sparkDF)
```

RESULTS

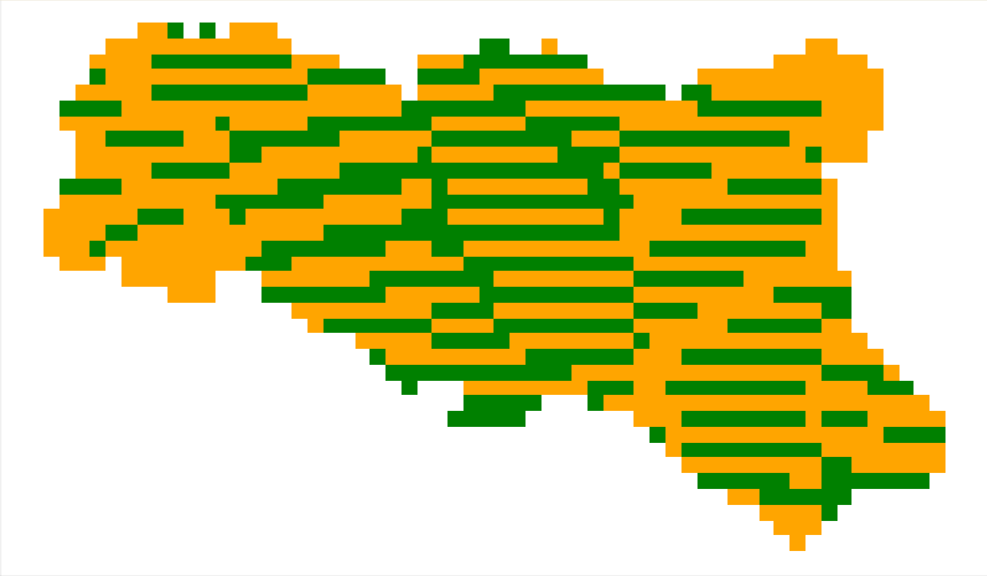
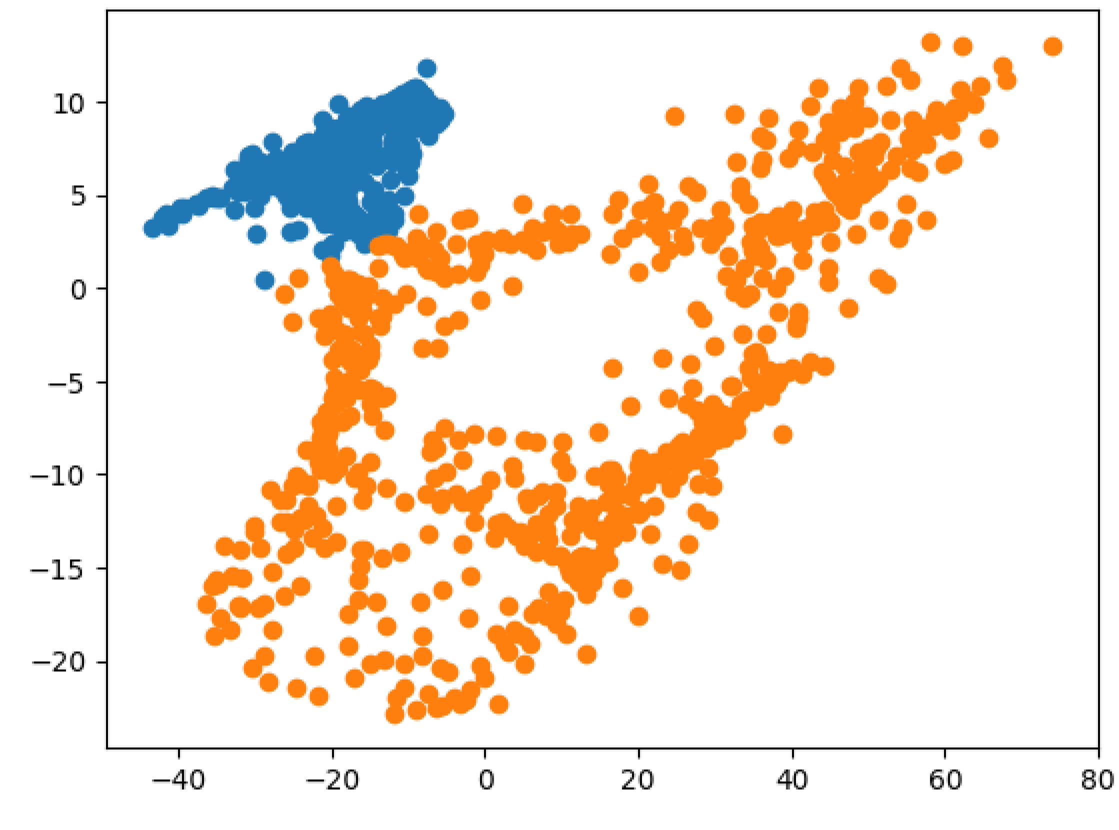
PRECIPITATIONS

K-Means PREC	Clusters
	
Silhouette: 0.67	Centers: (3.9 -0.55) (-24.66, 3.48)

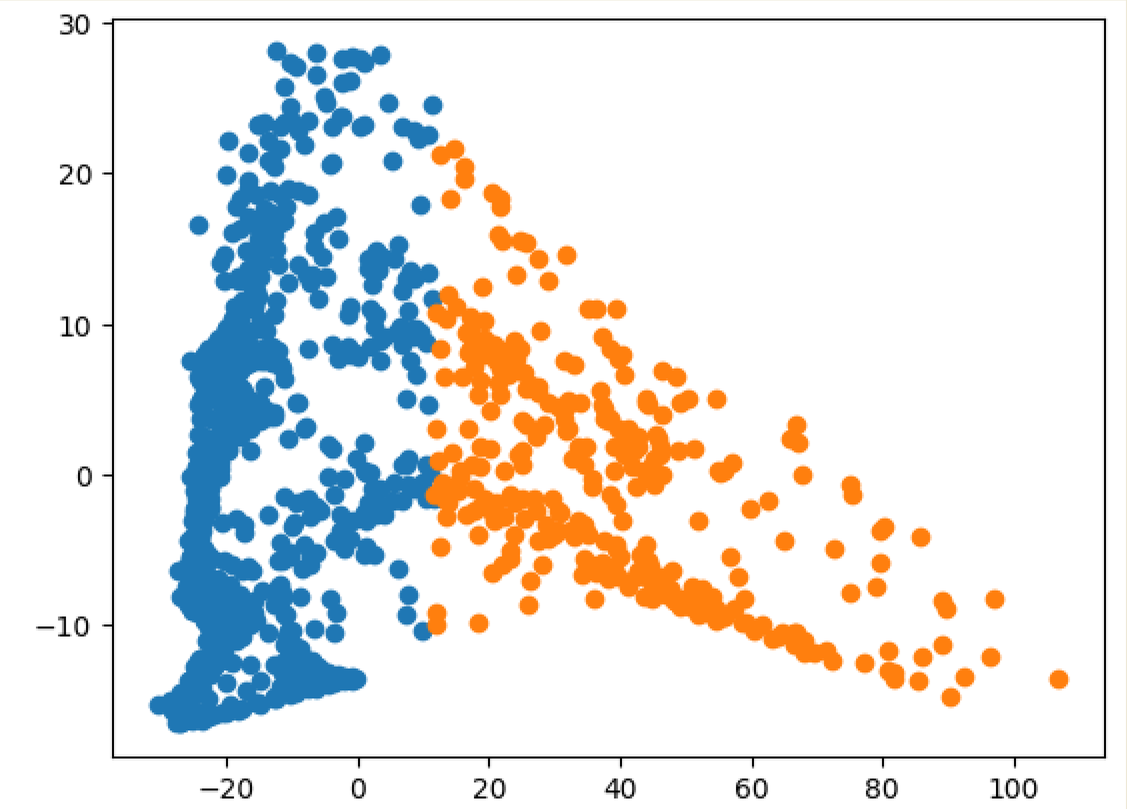
MIN TEMPERATURE - 1

K-Means	Clusters
	
Silhouette: 0.689	Centers: (-16.08, 0.69) (32.95, -1.60)

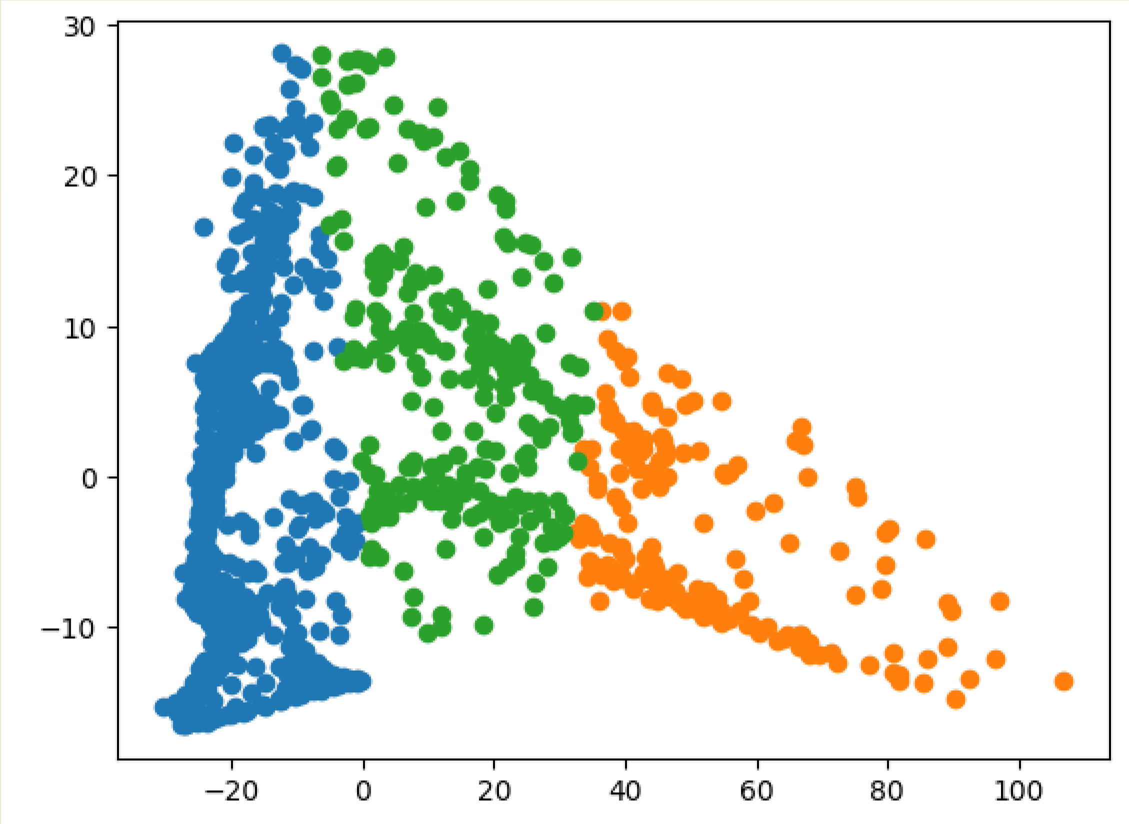
MIN TEMPERATURE - 2

GMM	Clusters
	
Silhouette: 0.305	

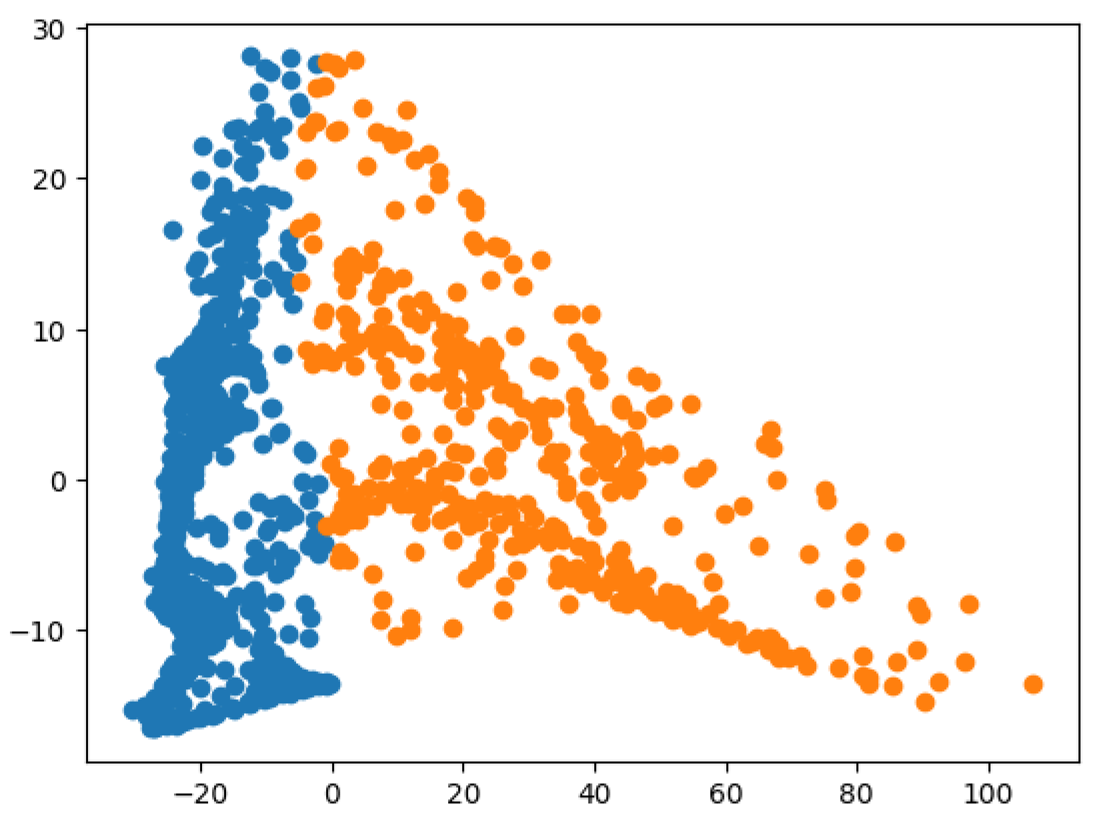
MAX TEMPERATURE - 1

K-MEANS	Clusters
	
Silhouette: 0.735	Centers: (-15.03, 0.14) (38.26, -3.65)

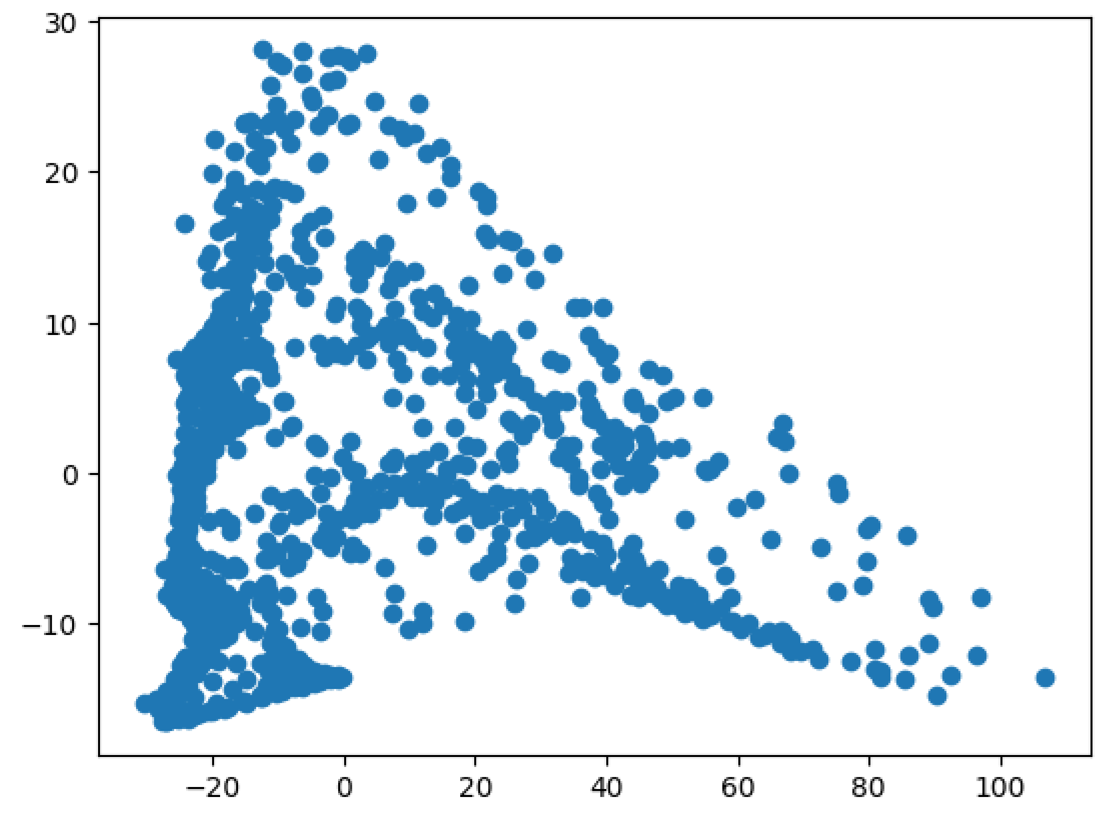
MAX TEMPERATURE - 2

K-MEANS	Clusters
	
Silhouette: 0.614	Centers: (52.19, -4.01) (13.87, 6.65) (13.87, 6.65)

MAX TEMPERATURE - 3

GMM	Clusters
	
Silhouette: 0.667	

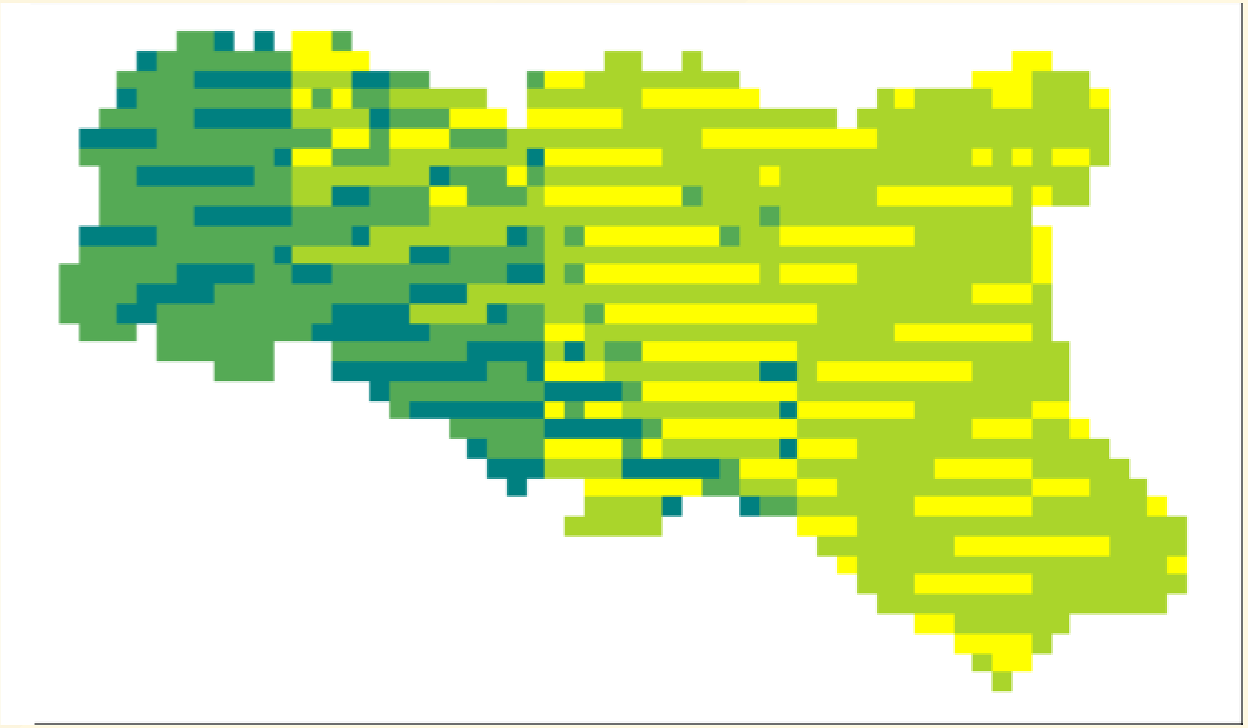
MAX TEMPERATURE - 4

Bisecting K-MEANS	Clusters
	

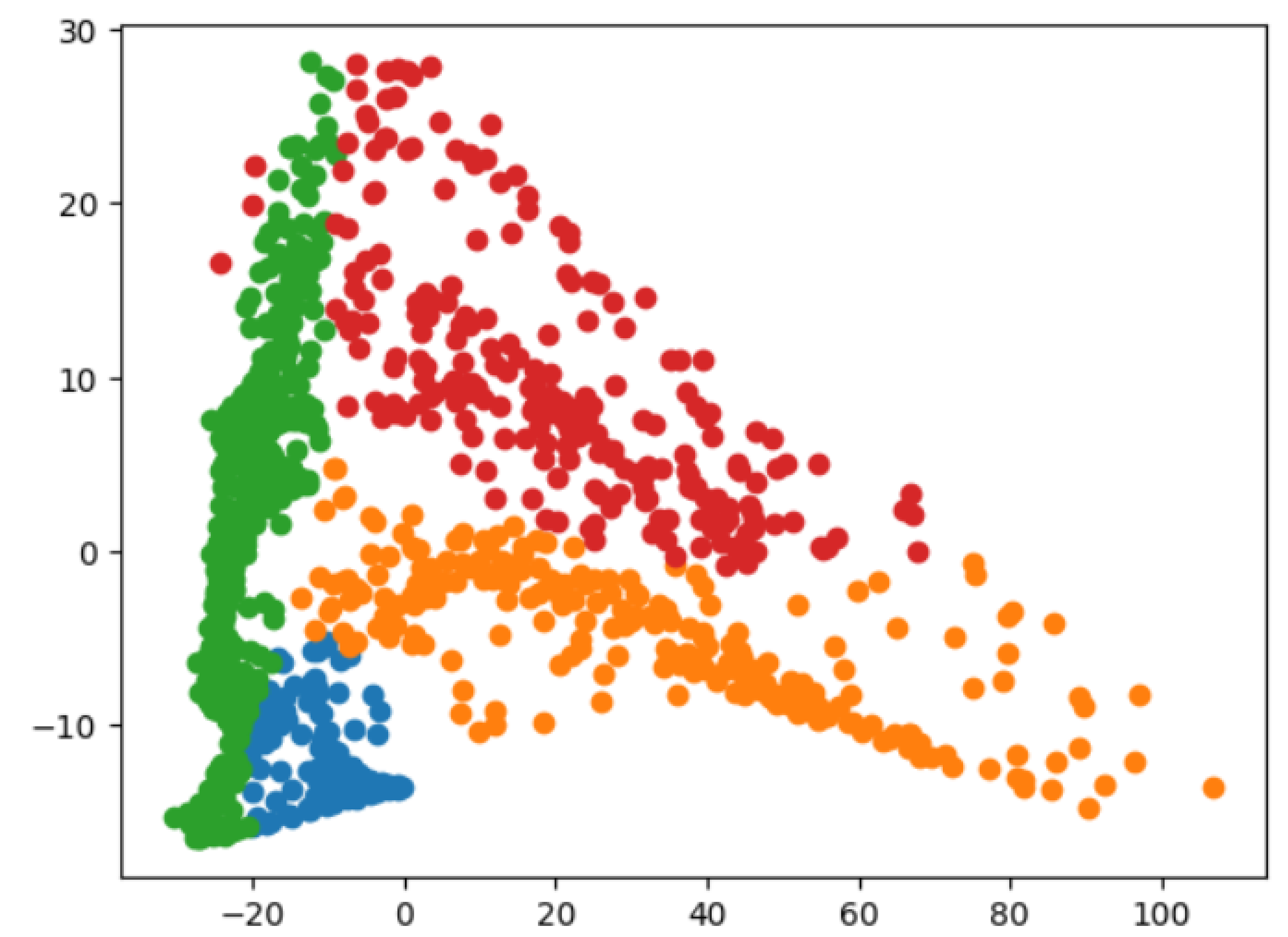
Best Results

Best Results

- Gaussian Mixture on TMAX Dataset using PCA (2 components) dividing the data in 4 clusters



Best Results



Improvements

- The PySpark MLlib K-Means implementation is only capable of using either cosine or euclidean distance as a measure for clustering.
- Since we had to work with euclidean distance the time-series data has been reduced to 2 dimensions using PCA (to avoid *curse of dimensionality* as much as possible), which, most likely, removed some relevant time-related features from the data.
- Applying Dynamic Time Warping as a metric on the series could be an interesting way to take time-related features into account (working on less agglomerated data).