ClusteringSolutions

September 11, 2018

1 Solutions to the Clustering Task

1.1 Problem 1

```
In [1]: Pkg.add("RDatasets")
        using RDatasets
        iris = dataset("datasets", "iris")
```

```
INFO: Package RDatasets is already installedINFO: METADATA is out-of-date  you may not have the
```

```
Out[1]: 150×5 DataFrames.DataFrame
```

Row	SepalLength	SepalWidth	PetalLength	PetalWidth	Species
1	5.1	3.5	1.4	0.2	"setosa"
2	4.9	3.0	1.4	0.2	"setosa"
3	4.7	3.2	1.3	0.2	"setosa"
4	4.6	3.1	1.5	0.2	"setosa"
5	5.0	3.6	1.4	0.2	"setosa"
6	5.4	3.9	1.7	0.4	"setosa"
7	4.6	3.4	1.4	0.3	"setosa"
8	5.0	3.4	1.5	0.2	"setosa"
9	4.4	2.9	1.4	0.2	"setosa"
10	4.9	3.1	1.5	0.1	"setosa"
11	5.4	3.7	1.5	0.2	"setosa"
139	6.0	3.0	4.8	1.8	"virginica"
140	6.9	3.1	5.4	2.1	"virginica"
141	6.7	3.1	5.6	2.4	"virginica"
142	6.9	3.1	5.1	2.3	"virginica"
143	5.8	2.7	5.1	1.9	"virginica"
144	6.8	3.2	5.9	2.3	"virginica"
145	6.7	3.3	5.7	2.5	"virginica"
146	6.7	3.0	5.2	2.3	"virginica"
147	6.3	2.5	5.0	1.9	"virginica"
148	6.5	3.0	5.2	2.0	"virginica"
149	6.2	3.4	5.4	2.3	"virginica"
150	5.9	3.0	5.1	1.8	"virginica"

```
In [4]: using Clustering
        features = Array(iris[:,[1,3,4]])'
        result = kmeans( features, 3 )
```

```
Out[4]: Clustering.KmeansResult{Float64}([6.81 5.006 5.89667; 5.7075 1.462 4.37167; 2.075 0.246
```

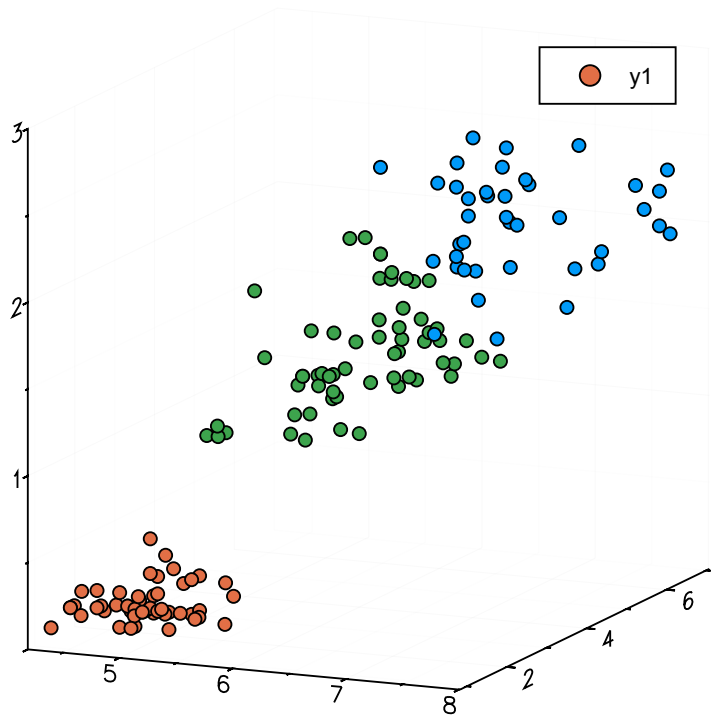
```
In [9]: features'
```

```
Out[9]: 150×3 Array{Float64,2}:
         5.1  1.4  0.2
         4.9  1.4  0.2
         4.7  1.3  0.2
         4.6  1.5  0.2
         5.0  1.4  0.2
         5.4  1.7  0.4
         4.6  1.4  0.3
         5.0  1.5  0.2
         4.4  1.4  0.2
         4.9  1.5  0.1
         5.4  1.5  0.2
         4.8  1.6  0.2
         4.8  1.4  0.1

         6.0  4.8  1.8
         6.9  5.4  2.1
         6.7  5.6  2.4
         6.9  5.1  2.3
         5.8  5.1  1.9
         6.8  5.9  2.3
         6.7  5.7  2.5
         6.7  5.2  2.3
         6.3  5.0  1.9
         6.5  5.2  2.0
         6.2  5.4  2.3
         5.9  5.1  1.8
```

```
In [20]: using Plots; gr()
         scatter(features[1,:], features[2,:], features[3,:], color = result.assignments)
```

```
Out[20]:
```



1.2 Problem 2 (Advanced)

The main clustering package for julia, is unexpectedly, named Clustering.jl - It supports K-means, K-medoids, Affinity Propagation, DBSCAN - It also supports hierarchical clustering, but that is not currently in the docs.

You'll also want Distances.jl for all your distance metric needs. It is traditional with word2vec to use cosine distance.

1.2.1 Affinity Propagraion

If you set the availability right, it can get a breakdown where the ball-sports and clustered seperately from the other sports. Though you may have problems with some of the cities being classes as sports, as this word2vec repressentation was trained on a dump of wikipedia taken in 2014, and there are a lot of sports pages talking about the Athens and Beijing olypics.

2 First we loadup some data

For the the example presented here, we will use a subhset of Word Embedding, trained using Word2Vec.jl. These are 100 dimentional vectors, which encode syntactic and semantic information about words.

```
In [1]: using Embeddings
        countries = ["Afghanistan", "Algeria", "Angola", "Arabia", "Argentina", "Australia", "
```

```
usa_cities = ["Albuquerque", "Atlanta", "Austin", "Baltimore", "Boston", "Charlotte",
world_capitals = ["Accra", "Algiers", "Amman", "Ankara", "Antananarivo", "Athens", "Bag
animals = ["alpaca","camel","cattle","dog","dove","duck","ferret","goldfish","goose","
sports = ["archery","badminton","basketball","boxing","cycling","diving","equestrian",

words_by_class = [countries, usa_cities, world_capitals, animals, sports]
all_words = reduce(vcat, words_by_class)
embedding_table = load_embeddings(Word2Vec; keep_words = all_words)
@assert Set(all_words) == Set(embedding_table.vocab)

embeddings = embedding_table.embeddings
all_words = embedding_table.vocab
classes = map(all_words) do word
    findfirst(col -> word  col, [countries, usa_cities, world_capitals, animals, sports
end;
```

In [3]:
```
display(all_words)
embeddings
```

```
185-element Array{String,1}:
 "China"
 "field"
 "Iraq"
 "Washington"
 "India"
 "South"
 "football"
 "Canada"
 "London"
 "England"
 "Australia"
 "Japan"
 "Pakistan"

 "taekwondo"
 "goldfish"
 "Las"
 "llama"
 "pentathlon"
 "alpaca"
 "Bogotá"
 "yak"
 "Antananarivo"
 "Brasília"
 "Usa"
 "Yaoundé"


300×185 Array{Float32,2}:
```

Out[3]:

```
 -0.0269732   -0.129657    0.0646846      -0.0523314    0.0111792
  0.0499904    0.0643991   0.042243         0.0302394    0.0545651
  0.0401002    0.0540952  -0.0221116        0.132239     0.0819807
  0.0305697   -0.128798    0.0202965       -0.0261657    0.099548
 -0.0471133    0.0152411  -0.0963669        0.00556217   0.0638811
 -0.0837969   -0.143395   -0.0346525      -0.011281    -0.0351346
  0.0557447    0.0097672   0.0396028       -0.0651793   -0.0915629
 -0.0168133   -0.129657   -0.118808        -0.0783405   -0.0460476
 -0.0240961    0.0119675  -0.0321773       -0.0463776   -0.0883688
  0.0126774    0.0403568   0.0676548        0.0152764    0.0282141
 -0.0517886    0.115918    0.0103132      -0.0523314   -0.0294119
 -0.00867639  -0.0755616  -0.00198014       0.100903     0.077722
  0.0906301    0.0807135  -0.000959131     -0.0927551    0.00367649

  0.00429324   0.0414301   0.105608        -0.0357232   -0.0670751
  0.0697708   -0.0157778   0.0295371        0.0457508   -0.0417889
  0.0517886    0.0328435  -0.0339924       0.0305528   -0.0117781
  0.0321881    0.104327   -0.0260719        0.0288293    0.000827626
  0.0561044   -0.139961   -0.041583        -0.0927551   -0.0123104
  0.0293109    0.0202857   0.0653447       -0.0460642   -0.0129758
  0.00233768   0.0880121  -0.0518137       -0.0399536   -0.0243547
 -0.0139362    0.0244717   0.0301972      -0.055465     0.0377963
 -0.0676129    0.0547392  -0.0587442       -0.0311795   -0.097951
  0.0507097   -0.0328435  -0.0184813       -0.0463776   -0.0351346
  0.0345258   -0.0139531   0.102307         0.0429306   -0.0473785
 -0.0293109    0.0377808   0.0358076        0.0374467    0.0686722
```

In [6]:
```
using Clustering
using Distances
using LinearAlgebra

similarity = 1f0 .- pairwise(CosineDist(), embeddings)
availability = 0.01*ones(size(similarity,1))
# tweaking availability is how you control number of clusters
# it is the diagonal of the similarity matrix
similarity[diagind(size(similarity)...)] = availability
aprop = affinityprop(similarity)
```

Out[6]:
```
AffinityPropResult([10, 28, 29, 34, 40, 52, 56, 62, 63, 77    114, 123, 124, 139, 143,
```

In [8]:
```
for (cluster_ii, examplar_ind) in enumerate(aprop.exemplars)
    println("-"^32)
    println("Exemplar: ", all_words[examplar_ind])
    cluster_member_inds = findall(assignments(aprop).==cluster_ii)
    println(join(getindex.([all_words], cluster_member_inds), ", "))
end
```

```
--------------------------------
Exemplar: England
```

London, England, Britain, Ireland, Wales

Exemplar: Atlanta
Detroit, Houston, Atlanta, Philadelphia, Dallas, Charlotte, Indianapolis, Memphis, Columbus, Na
---
Exemplar: Baghdad
Iraq, Afghanistan, Baghdad, Kabul, Cairo, Beirut, Riyadh, Amman
---
Exemplar: Seattle
Washington, Chicago, Boston, Seattle, Baltimore, Portland, Milwaukee, Sacramento
---
Exemplar: soccer
field, football, basketball, golf, soccer, hockey, tennis, rugby, wrestling, volleyball, handba
---
Exemplar: Moscow
Russia, Moscow, Ukraine, Baku, Minsk, Kyiv, Tashkent

Exemplar: Thailand
China, Japan, Singapore, Vietnam, Indonesia, Thailand, Malaysia, Philippines, Myanmar, Bangkok
---
Exemplar: Argentina
South, Canada, Australia, Germany, Spain, Italy, Brazil, Argentina, Venezuela, Colombia, Peru,
---
Exemplar: Tehran
Iran, Tehran, Damascus, Ankara

Exemplar: Bangladesh
India, Pakistan, Bangladesh, Nepal, Uzbekistan, Dhaka

Exemplar: Seoul
Beijing, Tokyo, Korea, Seoul, Pyongyang, Jakarta, Taipei, Hanoi
---
Exemplar: Uganda
Nigeria, Sudan, Kenya, Ghana, Uganda, Ethiopia, Tanzania, Nairobi, Mozambique, Kampala
---
Exemplar: Morocco
France, Egypt, Yemen, Algeria, Morocco, Arabia, Rabat

Exemplar: Santiago
Madrid, Manila, Santiago, Havana, Lima, Francisco, San, Caracas, Quito, Las, Bogotá

Exemplar: Albuquerque
Mexico, Denver, Phoenix, Austin, Fresno, Tucson, Omaha, Mesa, Vegas, Albuquerque
---
Exemplar: rat
mouse, duck, rat, goose, pigeon, ferret, goldfish

Exemplar: dove

```
shooting, diving, dove
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Exemplar: Budapest
Paris, Poland, Rome, Berlin, Athens, Vienna, Stockholm, Warsaw, Budapest, Bucharest
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Exemplar: rowing
swimming, cycling, sailing, fencing, gymnastics, rowing, equestrian, triathlon, kayak, pentathl
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Exemplar: Kinshasa
Congo, Khartoum, Pretoria, Accra, Madagascar, Algiers, Luanda, Kinshasa, Antananarivo, Brasília
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Exemplar: judo
boxing, archery, badminton, weightlifting, judo, taekwondo
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Exemplar: llama
dog, cattle, camel, llama, alpaca, yak
```