

DimensionalityReductionSolutions

September 1, 2018

1 Solutions to Dimensionality Reduction

2 Dimensionality Reduction Task

- Use PCA from [MultivariateStats.jl](#), to reduce 100 dimensional word embedding down to 3,2 and 1 dimensions.
- Plot these using [Plots.jl](#), coloring according to class

2.1 Tips:

- plotly is a good backend for 3D Plotting.
- The command `scatter(xs[1:], xs[2:], xs[3,]; hover=all_words, zcolor=classes)`
- will plot a 3D scatter plot
- coloring each point according to the numerical array `classes`
- and putting a tooltip on each point, according to the string array `all_words`

3 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 dimensional vectors, which encode syntactic and semantic information about words.

You can download the dataset from [here](#), and load it up with `JLD` as shown below. (or just load it directly if you have cloned the notebooks)

Example code for the loading, together with the words sorted into their original classes is below.

```
In [1]: using JLD
```

[illegible]

```
words_by_class = [countries, usa_cities, world_capitals, animals, sports]
```

```

all_words = vcat(words_by_class...)
classes = vcat(((1:5) .* ones.(length.(words_by_class))))...);
embeddings = load("../assets/ClusteringAndDimensionalityReduction.jld", "embeddings")

```

Out[1]: Dict{String,Array{Float32,1}} with 185 entries:

```

"ferret"      => Float32[0.0945707,-0.435267,0.0109875,-0.107674,0.169001,-0
"gymnastics"  => Float32[-0.269173,-0.343412,-0.00603042,-0.186179,0.0342606
"vegas"       => Float32[-0.00530534,-0.264874,0.0167432,-0.289836,-0.14033,
"archery"     => Float32[0.0279714,-0.485648,0.105468,-0.0696941,0.182807,-0
"jacksonville" => Float32[-0.418758,-0.0284594,0.00847164,-0.0989162,0.098186
"ankara"      => Float32[-0.139109,0.0872892,0.749557,-0.0308427,-0.0936718,
"pentathlon"  => Float32[-0.357405,-0.379595,-0.134314,-0.31008,-0.0245871,-
"seoul"       => Float32[0.0274904,-0.153844,-0.0936614,-0.0269344,-0.091449
"china"       => Float32[0.132423,-0.515862,-0.0381339,-0.287565,-0.285202,-
"korea"       => Float32[0.236904,-0.128355,-0.0816942,-0.0702621,-0.148426,
"argentina"   => Float32[-0.113967,-0.437523,-0.226014,-0.439572,-0.230062,-
"mozambique"  => Float32[0.309411,-0.13457,-0.632055,-0.309943,0.040591,0.11
"iraq"        => Float32[-0.260673,0.0356129,0.104878,0.103836,-0.17918,-0.3
"baku"        => Float32[0.182572,0.156322,0.225807,-0.0933851,-0.246997,-0.
"jakarta"     => Float32[0.13052,-0.408592,-0.0138496,-0.415052,0.21523,-0.0
"bogotá"      => Float32[-0.26368,-0.292844,-0.338501,-0.278793,-0.0690988,0
"sacramento"  => Float32[-0.217914,-0.116757,-0.213111,-0.13627,-0.0241341,-
"dhaka"       => Float32[-0.0264262,-0.256298,0.0922423,-0.711511,-0.329286,
"kyiv"        => Float32[-0.0527193,0.219892,-0.298013,-0.594799,-0.452732,-
"houston"     => Float32[-0.301442,-0.133911,-0.17504,-0.0391225,-0.0525875,
"italy"       => Float32[0.246153,-0.0510639,-0.143408,-0.149572,-0.229163,-
"francisco"   => Float32[-0.342338,-0.200734,-0.347174,-0.228947,-0.125513,-
"baghdad"     => Float32[-0.309163,0.00524779,0.287937,0.0294381,-0.173093,-
"dog"         => Float32[0.0509182,-0.479764,0.0209584,-0.0409415,0.0650602,
"kabul"       => Float32[-0.0282727,-0.108688,0.249284,0.119064,-0.163644,-0
=>

```

```

In [2]: using MultivariateStats
        using Plots
        plotly()

```

Out[2]: Plots.PlotlyBackend()

```

In [3]: embeddings_mat = hcat(getindex.(embeddings), all_words...)

```

```

Out[3]: 100E185 Array{Float32,2}:
 0.0386423 -0.0747454 -0.194131 -0.0949871 0.0184777
-0.0707636 0.00147601 -0.521243 -0.540243 -0.0992318
 0.122178 -0.030897 0.0806444 0.0674903 0.343439
 0.187411 -0.201719 -0.237717 -0.0968779 -0.113297
-0.215721 -0.181733 0.125805 0.277859 0.254373
-0.33405 -0.0827407 -0.202835 0.153194 0.359169
 0.198505 0.356985 -0.194464 -0.0815657 0.332574
 0.290666 0.204581 -0.210431 -0.253662 -0.548761

```

-0.264896	-0.240784	0.11638	0.295445	0.0797238
-0.370904	-0.276216	0.0468465	0.0898132	-0.0984195
-0.140316	-0.1886	0.180491	-0.147654	0.090978
-0.0271654	-0.336009	0.00966041	0.116254	0.163717
-0.245324	-0.002544	-0.381931	-0.646284	-0.321171
-0.426754	-0.0195873	-0.581407	-0.29744	-0.684529
0.194271	-0.265007	-0.319806	-0.430182	0.167392
0.0785286	0.14811	0.0619313	0.179959	-0.0968675
-0.401404	-0.247286	0.122847	0.146193	-0.17439
0.00592929	-0.063444	-0.0992176	0.211413	-0.111647
0.305375	0.0234759	0.00376886	0.0932082	0.0302637
-0.176298	-0.0396247	-0.103947	-0.0945107	-0.260385
0.0360829	-0.372389	-0.291512	-0.261196	0.148431
0.0877882	0.0802952	0.044897	0.347259	0.079031
-0.0831292	-0.18574	-0.127575	-0.0358119	-0.459085
0.0365798	-0.154143	-0.393261	-0.215115	-0.0123871
0.11823	-0.0554525	0.588549	0.334955	0.198312

```
In [4]: #Direct projection -- no DR -- just throw away the information in the other axes
xs=embeddings_mat
scatter(xs[1:], xs[2:], xs[3:]; hover=all_words, zcolor=classes)
```

3.0.1 PCA

```
In [5]: M = fit(PCA, embeddings_mat; maxoutdim=3)
xs = transform(M, embeddings_mat)
scatter(xs[1:], xs[2:], xs[3:]; hover=all_words, zcolor=classes)
```

```
In [6]: M = fit(PCA, embeddings_mat; maxoutdim=2)
xs = transform(M, embeddings_mat)
scatter(xs[1:], xs[2:]; hover=all_words, zcolor=classes)
```

```
In [7]: M = fit(PCA, embeddings_mat; maxoutdim=1)
xs = transform(M, embeddings_mat)
scatter(xs[1:], ones(length(xs)); hover=all_words, zcolor=classes)
```

4 ICA

```
In [8]: embeddings_mat_f64 = convert(Matrix{Float64}, embeddings_mat)
```

```
M = fit(ICA, Float64.(embeddings_mat_f64),5)
xs = transform(M, embeddings_mat_f64)
```

```
Out[8]: 5E185 Array{Float64,2}:
-0.449666  0.0614239 -0.0577035  2.71363  3.16895  1.36657
 0.15085  1.48484  2.47812  -0.382752  0.0210489 -0.613272
 1.64663  1.68168  -0.381274  -0.0461585  0.0635969 -0.377507
```

```

0.667897  0.0681079 -0.802374    -0.18597    0.436981    0.401189
0.839049 -0.145083  -0.0118368    -0.381903   -0.159733   -0.789554

```

```
In [9]: scatter(xs[1,:], xs[2,:], xs[3,:]; hover=all_words, zcolor=classes)
```

5 Extension: T-SNE

- Use [TSne.jl](#), to perform similar dimentionality reduction, and to produce plots.

T-SNE is another popluar DR method.
 However, the [TSne.jl](#) package is not registered.
 It is mostly maintained though. Be warned: it is sideways -- it is row major, so tanspose the inputs and outputs

You may have to play with the perplexity to get it to work well.

If you look at the resulting plots, you may note that countries are often paired uo with their captical city.

```
In [10]: using TSne
```

```
In [12]: xs = tsne(embeddings_mat', 3, 500, 1000, 20.0)'
```

```
Computing point perplexities100%|| Time: 0:00:00
```

```
WARNING: could not attach metadata for @simd loop.
WARNING: could not attach metadata for @simd loop.
```

```
Computing t-SNE 0%| | ETA: 0:05:31Computing t-SNE 1%|
```

```
Out[12]: 3E185 Array{Float64,2}:
```

```

18.5321 -3.90908 -25.9997    2.78249    18.8778    35.9635    30.5813
34.581  16.4268  -0.117784  34.6205    15.4415    -1.16452   -25.0301
30.7113 36.721   54.6548   40.7141   -50.6902  -49.7441   -38.8731

```

```
In [14]: scatter(xs[1,:], xs[2,:], xs[3,:]; hover=all_words, zcolor=classes)
```