A Clustering Approach to detect Dependencies between Test Cases

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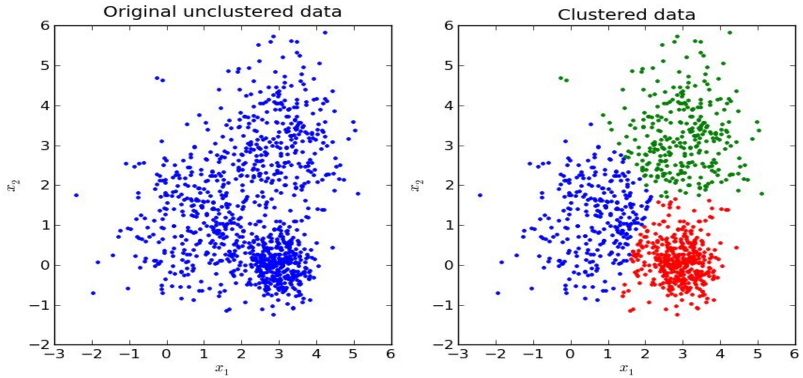
Introduction



Assignment Description

Ground Truth

TC	DependsOn
TC0000	TC0001
TC0000	TC0002
TC0001	TC0002
TC0018	TC0019
TC0018	TC0020
⋮	⋮

Data as 64-dimensional vectors

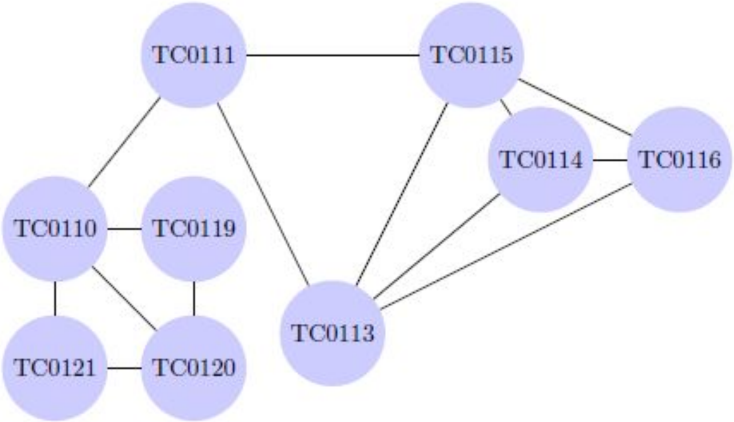
TC	d_0	d_1	$\cdots$	d_{63}
TC0000	1.3540313243865967	-0.3458509147167206	$\cdots$	-0.526816725730896
TC0001	1.1611902713775635	-0.2490767240524292	$\cdots$	-0.6400560736656189
TC0002	1.0486541986465454	-0.11896729469299316	$\cdots$	-0.48657703399658203
⋮	⋮	⋮		⋮

Aim : Find the best algorithm to cluster the high dimensional feature vectors

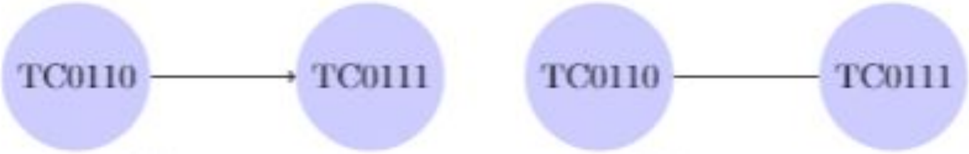
How: Evaluate performance of different clustering methods through evaluation metrics

Assumptions

- Not-overlapping clustering



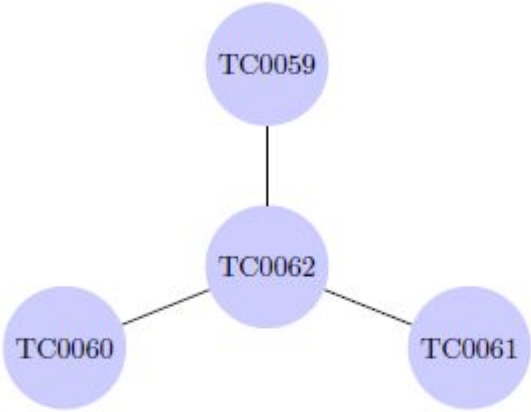
- Bidirectional dependencies

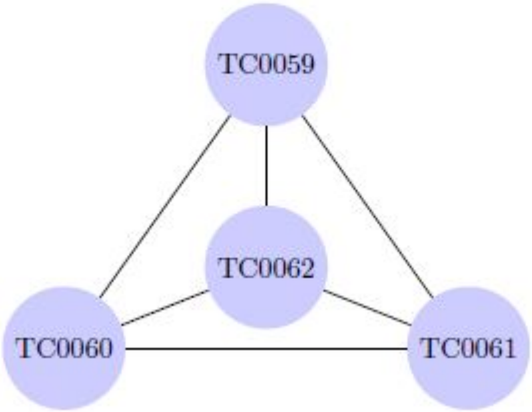


((a)) Directional ((b)) Bidirectional

Assumptions

- Transitive Dependencies within GT Clusters





- Each TC must be assigned to one and only one cluster - specific for K-Means

Method

1. Import High Dimensional Data
2. Format GT to get clusters accordingly to Assumptions
3. Compute Indep List
4. If wanted, perform PCA to maintain 80% variability
5. Run Clustering Algorithm
6. Compute Result Matrix
7. Evaluate results

Performance Analysis

Algorithm 5 Detection of TP and FN pairwise instances

```
Data: Results matrix and formatted Ground Truth GT.csv
Result: TP and FN
initialization to 0 for TP and FN
for every TC do
    for every line in GT.csv do
        if TC is in line then
            for every element in line do
                if element != TC and element > TC then
                    if they have same label in Results different from -1 then
                        TP += 1
                    else
                        FN += 1
                    end
                end
            end
        end
    end
end
```

Performance Analysis (Cont'd)

Algorithm 6 Detection of FP pairwise instances

Data: Results matrix & formatted Ground Truth `GT.csv` & `Indep` list
Result: FP

```
initialisation to 0 for FP
for every pair of TCs i,j do
    if j > i then
        if i,j have same label in Result & this label is not -1 then
            for each line in GT.csv do
                if i is in the line but j not then
                    FP += 1
                end
            end
        end
    end
end
for every pair of TCs i,j do
    if j > i then
        if i,j have same label in Result & this label is not -1 then
            if i & j are both in Indep then
                FP += 1
            end
        end
    end
end
```

Performance Analysis (Cont'd)

Pairwise labeling

- Not ordered combinations w/o repetition
- ">" condition to avoid double counting
- TP + FN fixed sum

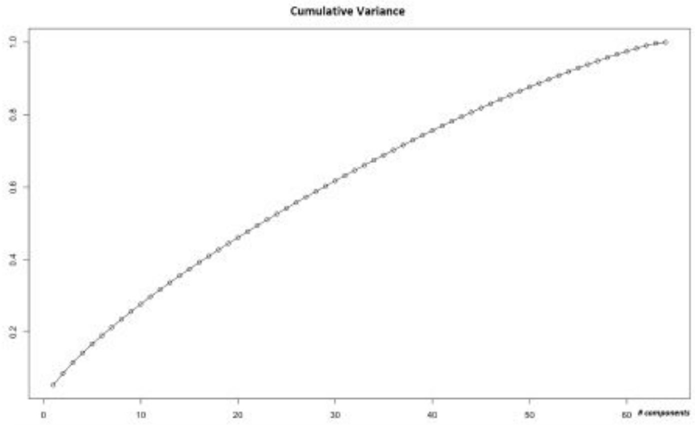
$$TP + FN = \sum_{i=1}^{NR} \binom{n_i}{2}$$

- TN = N - (TP + FN + FP)

$$N = \binom{1748}{2} = 1526878$$

-1 labeling → valid only for HDBSCAN

PCA Procedure



- Linear increasing rate
- 80% variability → 44 components.

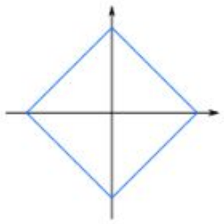
Parameter Selection

K-Means

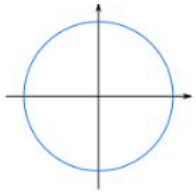
- K = {400,600,800,1000,1200}

HDBSCAN

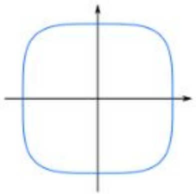
- **Distance:** Canberra, Manhattan, Euclidean & Minkowski (p=4)
- **Alpha:** distance tuning parameter → a = {0.75,1.0,1.2}
- **Min Cluster Size:** MCS = {2,3}
- **Cluster Selection Method:** granularity of clusters → {eom,leaf}



Manhattan (p=1)



Euclidean (p=2)



Minkowski (p=4)

Results – Tables

K-Means

- Without PCA

K	Recall	Precision	F-measure
400	0.093	0.036	0.052
600	0.156	0.313	0.216
800	0.176	0.009	0.016
1000	0.165	0.007	0.013
1200	0.189	0.008	0.015

- With PCA

K	Recall	Precision	F-measure
400	0.086	0.187	0.118
600	0.155	0.310	0.207
800	0.171	0.008	0.016
1000	0.189	0.008	0.015
1200	0.170	0.474	0.250

HDBSCAN

- Without PCA

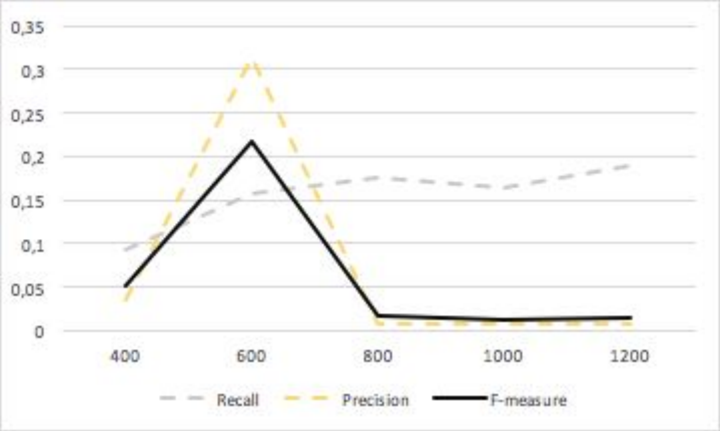
Distance	Alpha	Min Cluster Size	Cluster Selection Method	Recall	Precision	F-measure
Canberra	0,75 & 1,0	2	eom	0,261	0,269	0,265
Canberra	0,75 & 1,0	2	leaf	0,223	0,301	0,256
Canberra	0,75	3	leaf	0,280	0,252	0,265
Euclidean	0,75 & 1,0	2	leaf	0,233	0,449	0,307
Euclidean	0,75	3	eom	0,305	0,315	0,310
Euclidean	1,2	3	eom	0,957	0,002	0,005
Euclidean	0,75	3	leaf	0,290	0,391	0,333
Manhattan	0,75 & 1,0	2	eom	0,243	0,323	0,277
Manhattan	1,2	2	eom	0,217	0,444	0,292
Manhattan	1,2	2	leaf	0,201	0,627	0,304
Manhattan	0,75	3	eom	0,296	0,325	0,309
Manhattan	1,0	3	eom	0,256	0,394	0,310
Manhattan	0,75	3	leaf	0,270	0,405	0,324
Minkowski	0,75 & 1,0	2	leaf	0,233	0,449	0,307
Minkowski	0,75	3	eom	0,305	0,315	0,310
Minkowski	1,2	3	eom	0,957	0,002	0,005
Minkowski	0,75	3	leaf	0,290	0,391	0,333

- With PCA

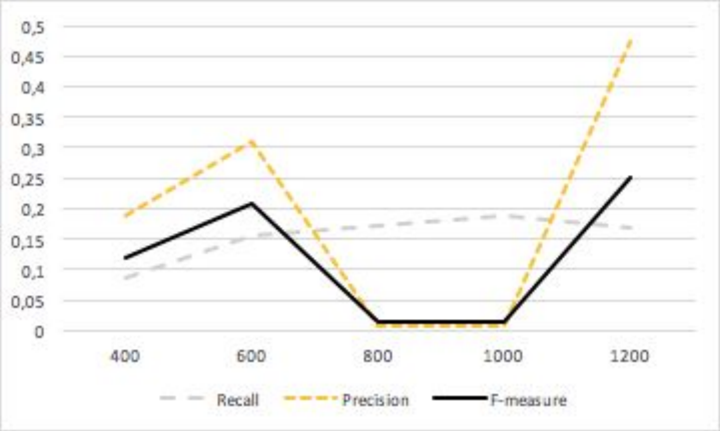
Distance	Alpha	Min Cluster Size	Cluster Selection Method	Recall	Precision	F-measure
Canberra	0.75 & 1.0 & 1.2	2	eom	0.254	0.290	0.271
Canberra	0.75 & 1.0 & 1.2	2	leaf	0.227	0.278	0.250
Euclidean	0.75 & 1.0 & 1.2	2	eom	0.244	0.377	0.296
Euclidean	0.75 & 1.0 & 1.2	3	eom	0.997	0.002	0.003
Manhattan	0.75 & 1.0 & 1.2	2	eom	0.238	0.431	0.306
Manhattan	0.75 & 1.0 & 1.2	3	eom	0.999	0.002	0.003
Manhattan	0.75 & 1.0 & 1.2	2	leaf	0.184	0.391	0.250
Minkowski	0.75 & 1.0 & 1.2	2	eom	0.244	0.377	0.296
Minkowski	0.75 & 1.0 & 1.2	3	eom	0.997	0.002	0.003

Results - K-means

K-means without PCA

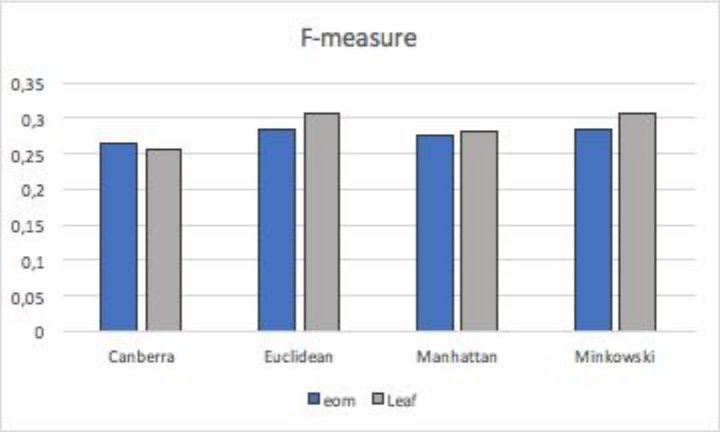


K-means with PCA

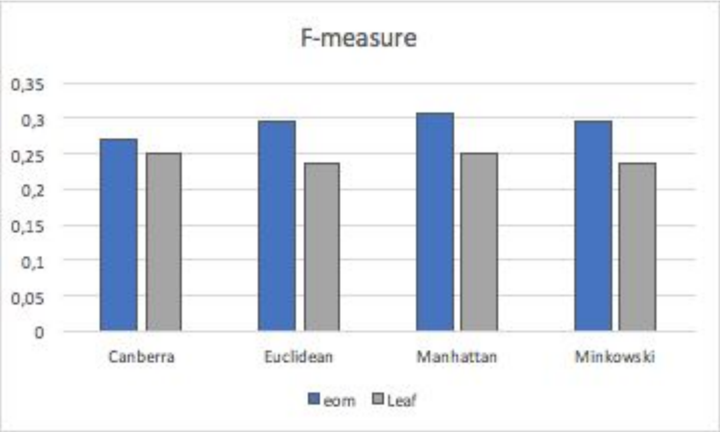


Results – HDBSCAN

HDBSCAN (alpha = 1, MinClusterSize = 2)
Without PCA



HDBSCAN (alpha =1 MinClusterSize = 2)
With PCA



Analysis - K-Means

- Generally weaker results

- Advantages
  - Relatively fast iteration

- Disadvantages
  - To be run over more iterations
    - Offsets speed advantage over HDBSCAN
  - Value of Clusters must be known beforehand
  - Only ideal for capturing ‘globular’/spherical clusters
  - Poorer performance in capturing clusters of varying variance
  - Does not separate outliers/noise/independent data

Analysis – HDBSCAN

- Generally More Reliable
  - More consistent, better results
  - Separate outliers/noise/independent data
  - More parameters can be changed
  - Does not need multiple instances
    - Global Optimum found
    - Reproducible by external parties
- Considerations
  - Still does not capture large clusters in its entirety

Analysis – is PCA good?

- **Different parameters → different behaviour**
- K-Means:
  - K=600 worsening using PCA
  - K=1200 improvement using PCA

- HDBSCAN:
  - Canberra [2,eom] → improvement using PCA
  - Canberra [2,leaf] → worsening using PCA
  - Manhattan[2,eom] → best results in PCA
  - More degenerate cases

- Best K-Means F-Measure if using PCA
- Best HDBSCAN F-Measure if *not* using PCA

It depends on:

- Parameters
- Requirements

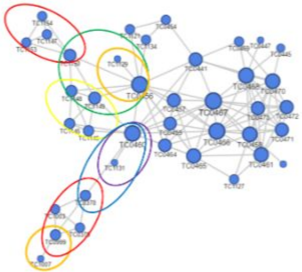
Discussion & Improvements

- Limitations of Current Algorithms
  - Non-overlapping Clusters
    - Highly Restrictive in Clustering
  - Direct/Directional Dependencies not Shown
    - Further Processing Required

- Limitations of Performance Metric
  - Precision & Recall equal weightage
    - May be different in reality
  - Effect of True Negatives is ignored
    - Only TP, FP, and FN taken into consideration
  - Size of Positive/Negative allocations in clustering not considered
    - Size of dependent/independent results may skew performance metrics

Discussion & Improvements (Cont'd)

- Use of other algorithms
  - Fuzzy C-Means
    - "Upgrade" from K-Means
    - Degree of membership into clusters
    - More flexible than K-Means/HDBSCAN



  - Subspace Clustering Methods
    - Forms clusters in data's subspaces
    - 'Noise' from irrelevant dimensions removed/ignored
    - SUBCLU, CLIQUE, DOC, MAFIA

- Use of other metrics/indexes
  - F_β Scores - Different weightage of Precision/Recall

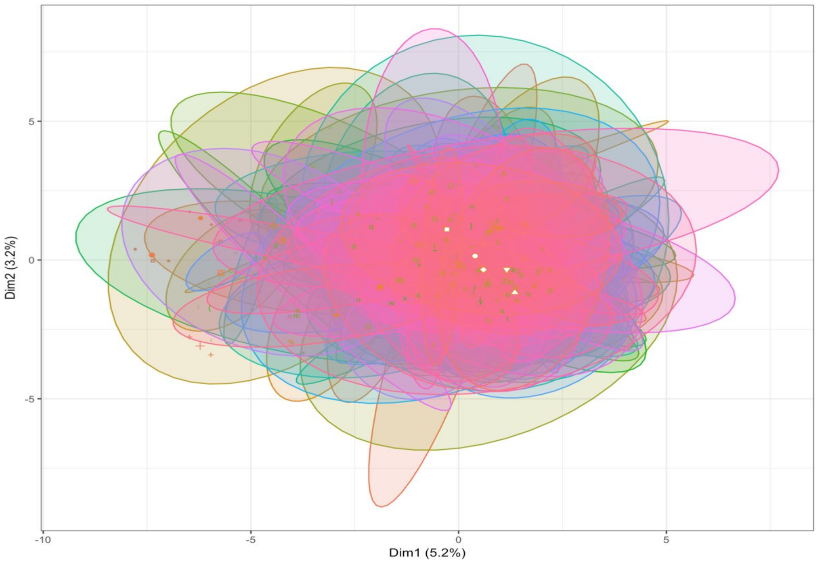
Distance	PCA	Alpha	MCS/K	CSM	F_1 Score	$F_{0,5}$ Score	F_2 Score
K-Means	Yes	N.A.	1200	N.A.	0,250	0,349	0,195
Minkowski	No	0.75	3	leaf	0.333	0,366	0,306
Manhattan	No	1,2	2	leaf	0,304	0,440	0,233
Manhattan	Yes	1,0	2	eom	0,306	0,371	0,261
Minkowski	No	0,75	3	eom	0,310	0,313	0,306
Canberra	Yes	1,0	2	eom	0,271	0,282	0,260

  - Matthew's Correlation Coefficient (MCC) - Prioritises True Positives and True Negatives equally

Distance	PCA	Alpha	MCS/K	CSM	TP	FP	FN	TN	F_1 Score	MCC Score
K-Means	Yes	N.A.	1200	N.A.	264	293	1.289	1.525.560	0,250	0,283
Minkowski	No	0.75	3	leaf	451	703	1.102	1.524.622	0.333	0,484
Manhattan	No	1,2	2	leaf	312	186	1.241	1.525.139	0,304	0,335
Manhattan	Yes	1,0	2	eom	369	488	1.184	1.524.837	0,306	0,396
Minkowski	No	0,75	3	eom	473	1.027	1.080	1.524.298	0,310	0,507
Canberra	Yes	1,0	2	eom	394	963	1.159	1.524.362	0,271	0,422

Q&A and some very intuitive plots

K-Means



HDBSCAN