Anomaly detection interpretation based on Mahalanobis distance decomposition

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Outline:

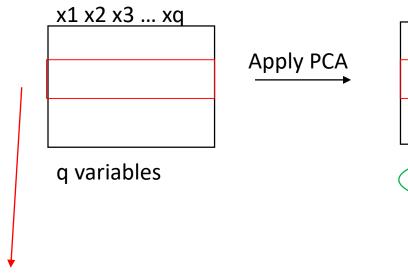
- 0) Introduction
- 1) Training
- 2) Gaussian mixture Fitting
- 3) Mahalanobis distance computation
- 4) Minimum Mahalanobis distance computation
- 5) Check if the distance is under the threshold
- 6) Minimum Mahalanobis distance decomposition
- 7) Define the starting variable more responsible for the anomaly

0) Introduction

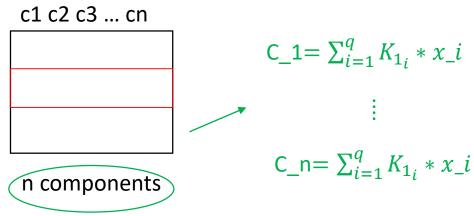
- **PCA** can be seen as a simpler autoencoder
- Going in another space(components), coming back(starting variables) and computing the *error in recostruction* can detect anomalies (when there is a big error we raise an alert)
- Fitting the nominal data with a **set of Gaussian** allows to create a more reliable model
- Decomposing the *mahalanobis distance* it possible to retrive the initial variables

1) Training

Dataset Training X_train



One time instance



PCA loggings

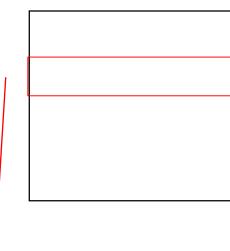
K11	 K1q
Kn1	 Knq

OUTPUT 1

2) Gaussian mixture fitting

Dataset Training Transformed C

c1 c2 c3 ... cn



Fit mixture with m Gaussian

i = 1...m

$$\mu_i = [\mu_1_i, ..., \mu_c_i]$$

$$\sum_{i} = diag(\sigma_1_i, ..., \sigma_c_i)$$

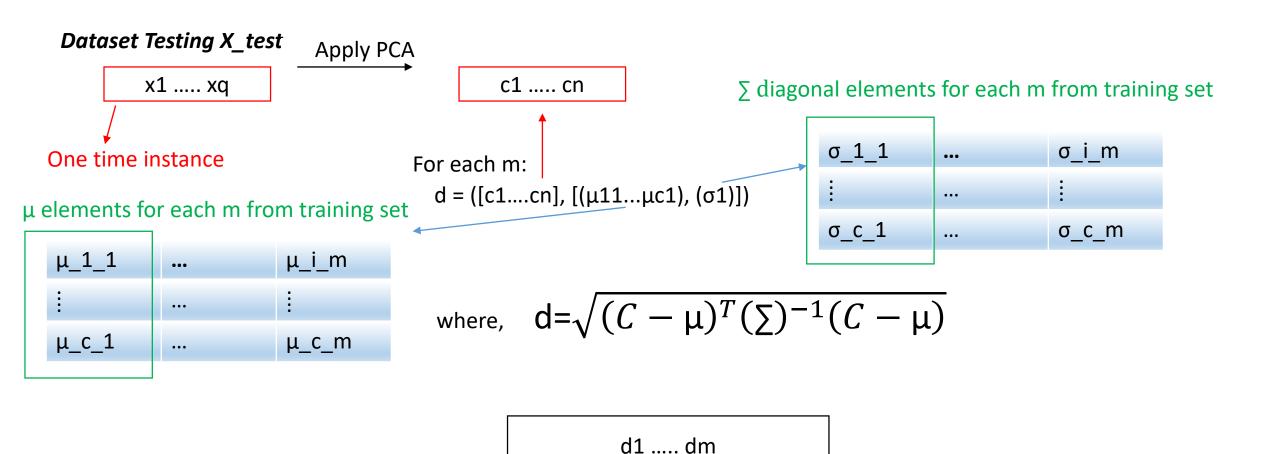
One time instance

μ_1_1	•••	μ_i_m	
		•	
μ_c_1		μ_c_m	

σ_1_1	 σ_1_m
	 •
σ_c_1	 σ_c_m

OUTPUT 2

3) Mahalanobis distance computation



OUTPUT 3

4) Minimum Mahalanobis distance computation

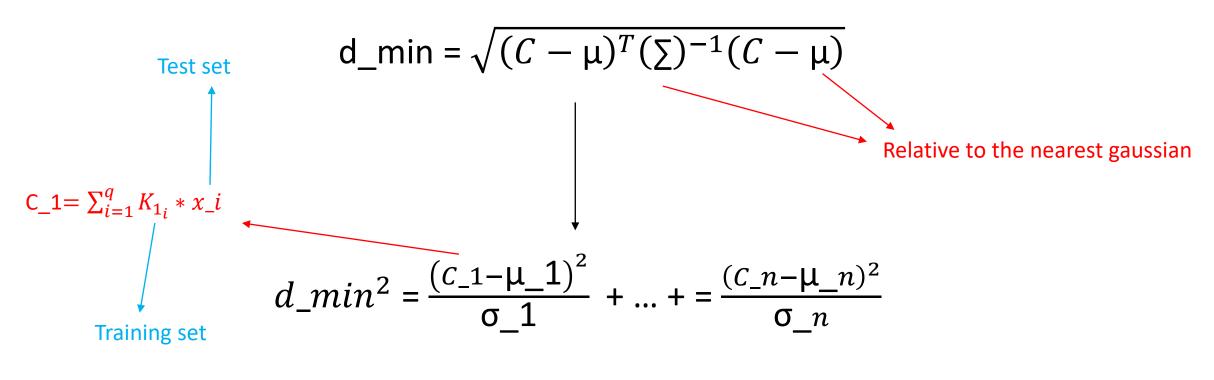


5) Check if the <u>distance</u> is under the threshold

If d_min > THRESHOLD ANOMALY DETECTED!

OUTPUT 5

How did we decompose the distance?



$$d_{min}^2 = f(x) + f(\mu)$$

6) Minimum Mahalanobis distance decomposition

$$d_{min}_{finale} = d_{min}^2 - \sum_{i=1}^q \mu_i^2$$

 $A_x_i^2$

For each i=1,, q

OUTPUT 6

 A_x_i

For each i=1,, q

 $A_x_ix_j$

For each i=1,, q with $i \neq j$

7) Define the starting variable more responsible for the anomaly

Search the bigger |A_*| and define the related x_i

OUTPUT 7

How do we decide if the |A_*| is enough big?

For each |A_*| is used a threshold based on *mean* and *standard deviation* computed on nominal |A_*|.

Example

```
q variables = 4, n components = 3, mixture=5 ANOMALY \rightarrow q=4
K components
 [-0.46182718 -0.5591836 \ 0.6551106 -0.21180051]
 [-0.33681882 -0.41828449 -0.34570756 0.76946569]
 [ 0.82035696 -0.49709971 0.21379657 0.18492528]]
                VEL LIN LS LC
                                               LD
DATASET TEST [0.26173008 6.54661097 0.6605
                                                5.022111031
DATASET TEST AFTER PCA [ -4.412617 0.809501 -1.969678]
 RESULT
x1^2 - x2^2 - x3^2 - x4^2
[0.008695936764374215, 48.24616801989206, 0.5818851660326526, (124.30340628217398)]
x1 - x2 - x3 - x4
[-0.6186189056274868, 79.90366203485536, -0.6952100181715678, (-108.64032194935119)]
x1 x2 - x1 x3 - x1 x4 - x2 x3 - x2 x4 - x3 x4
[-0.20991945107618623, 0.03354080910481509, -0.14702507822337377, -2.264383404426474,
-81.03373527567052, -9.631450904620603)
```

Example

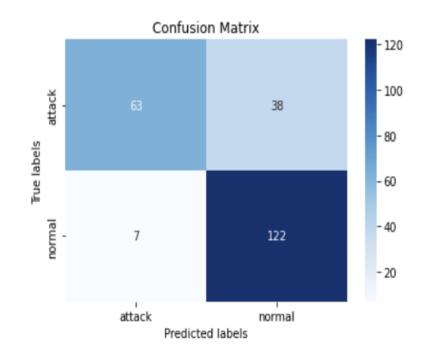
X1^2	0.005376593658132822	0.01406528277371126	564.3575118429884	0.002196104282187567
X2^2	0.040022072775998334	320.10897652642507	0.7930072409584044	0.36852173286333867
X3^2	193.25887720279718	0.3754555508489652	0.5067394335545415	0.22720295203060326
X4^2	0.45034457752432877	1.5386103458720952	0.2849199979105846	340.83840098506346
X1	0.054911344699514836	0.0888142607471055	-33.38083180975043	0.0658485898436691
X2	-0.08925692813758927	-7.98253945611004	5.232223899516044	3.566804419599815
X3	-54.17268150656344	2.3877555988058226	-0.6171273657751212	-0.4132277125747382
X4	-2.3068927546455718	4.26402026740884	-3.1143331960345266	-107.7154173109028
X1X2	0.008552019287260062	1.2370533667432237	[2.684127741816416	-0.003609486991530586
X1X3	-0.7532365886426685	0.05369842807563012	-0.5898713514139415	0.0007791503364421645
X1X4	-0.00803356603166589	0.024017115638546523	-2.6145577138339178	0.17838582884391493
X2X3	-1.2928885479482584	5.096473437770478	0.5090851031898308	0.2323795995184279
X2X4	0.17111227973470042	-28.286041254294155	-0.4534104177139992	-10.690481434188866
X3X4	11.209345586500177	0.9132331182282317	0.4657955320045161	10.787548116360082

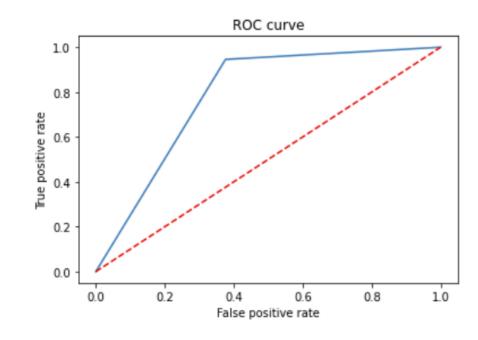
Example (summing up the terms)

0.06028794 -0.04923486 139.0861957 - 1.85654818 0.10287954 312.12643707 2.76321115 5.80263061

530.97668003 6.02523114 -0.11038793 -2.8294132 0.06804469 3.93532615 -0.18602476 233.12298367

Overall result





Results and next challenges

- The accuracy is around 80%
- In most cases the system is able to give the right interpretation to the anomaly
- Find a smarter criteria for the THRESHOLD
- Investigate how the number of components are related to the interpretation, is there a limit?
- Define the nominal model with another kind of distribution

Thank you for your attention

Question??