Parcours Datascientist : projet 5

Segmentation d’une clientèle

Basée sur un relevé de factures

Francois BANGUI

Parcours Datascientist : projet 5

Annexes

Annexe 1 : fichiers du projet

Annexe 2 : organisation et processus de l’étude

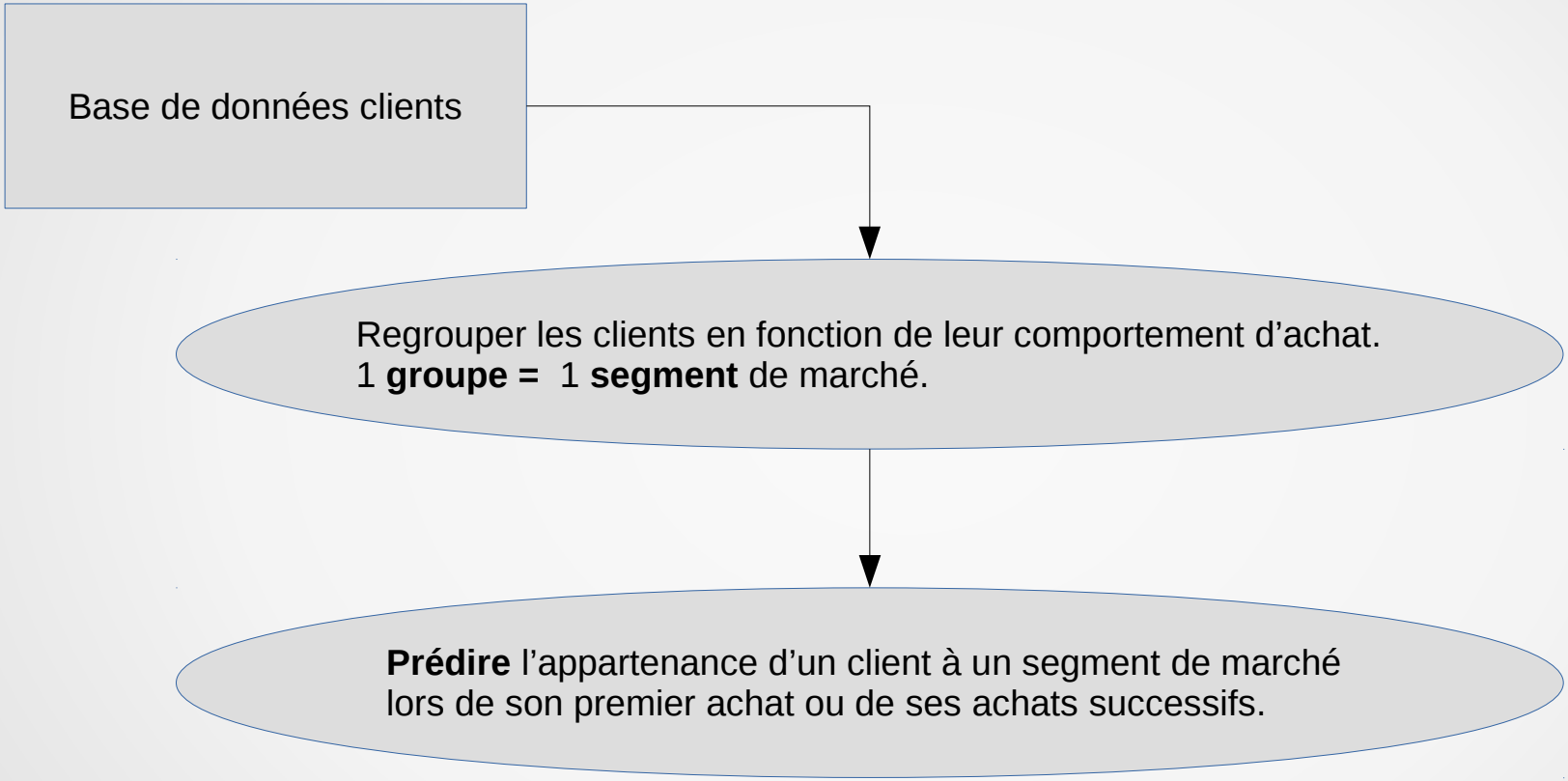
Annexe 3 : Variables issues du score RFM

Annexe 4 : variables issues du traitement NLP

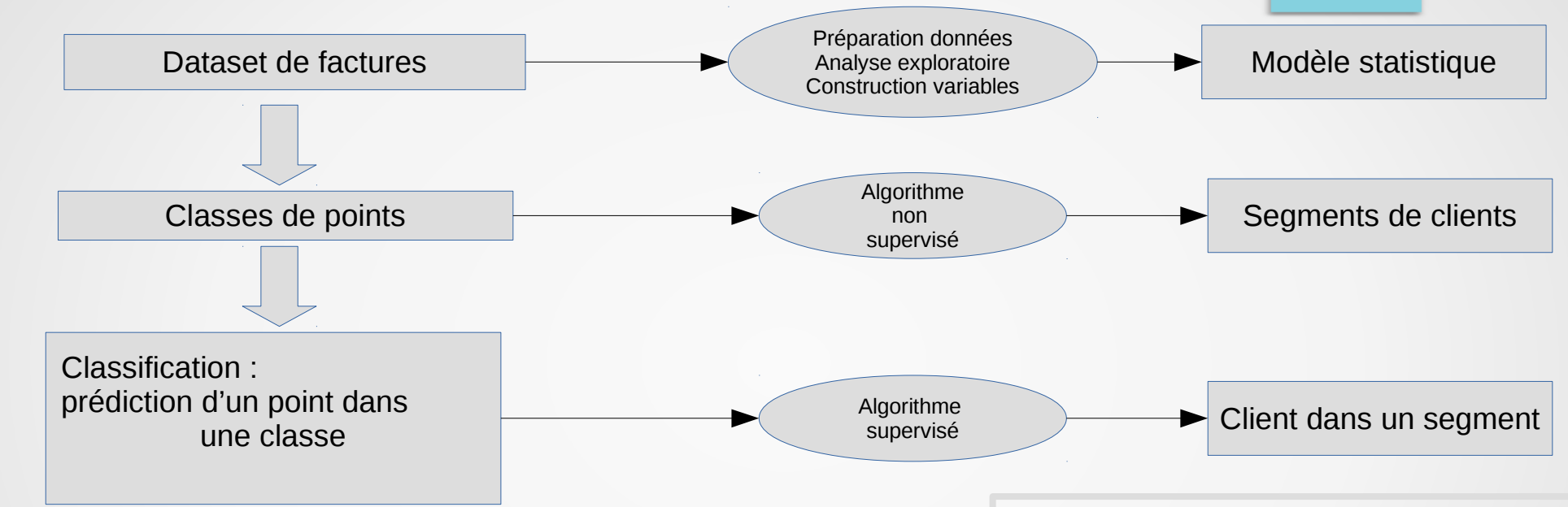
Annexe 5 : variables issues de la date de facturation

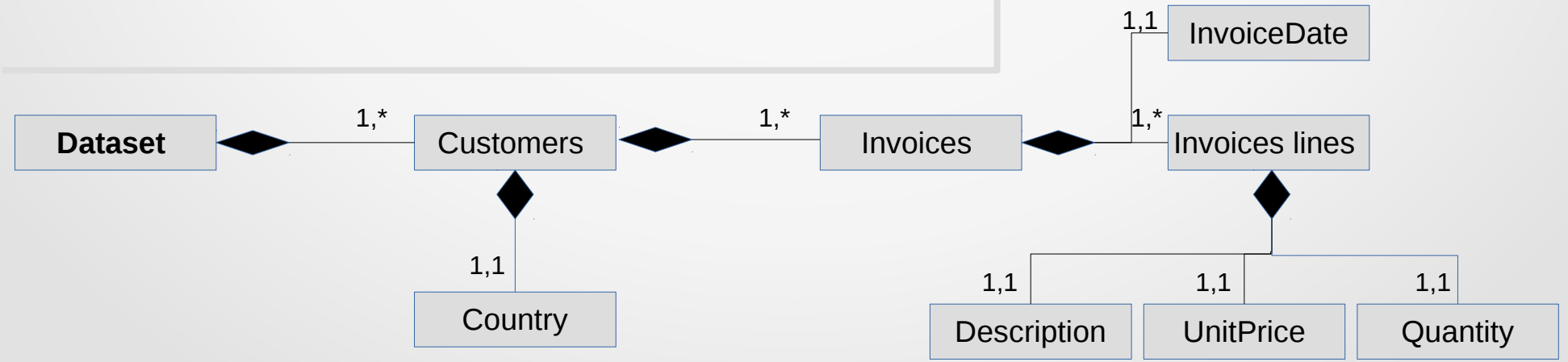
Annexe 6 : API WEB

Formulation du problème : mission

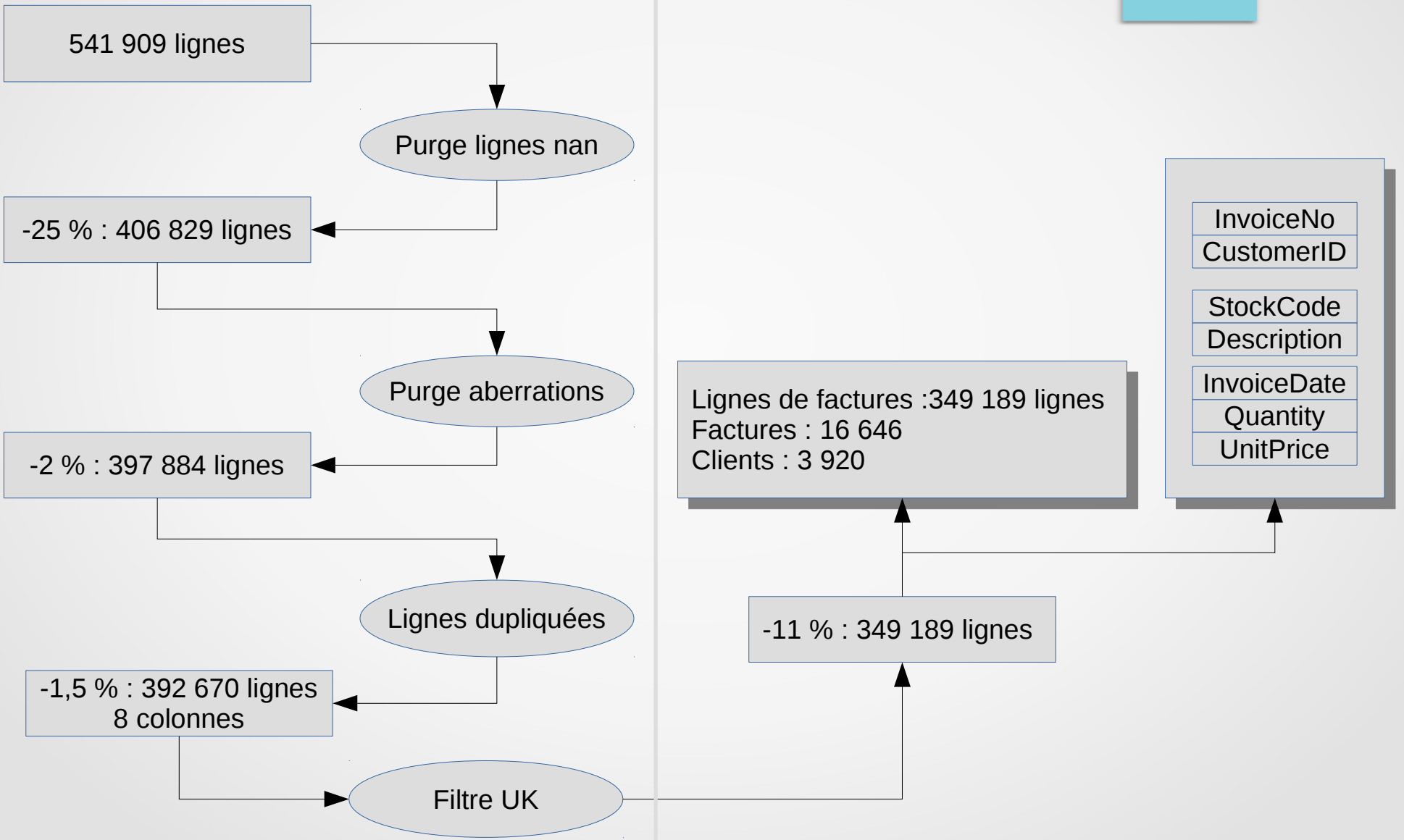


Processus global du projet

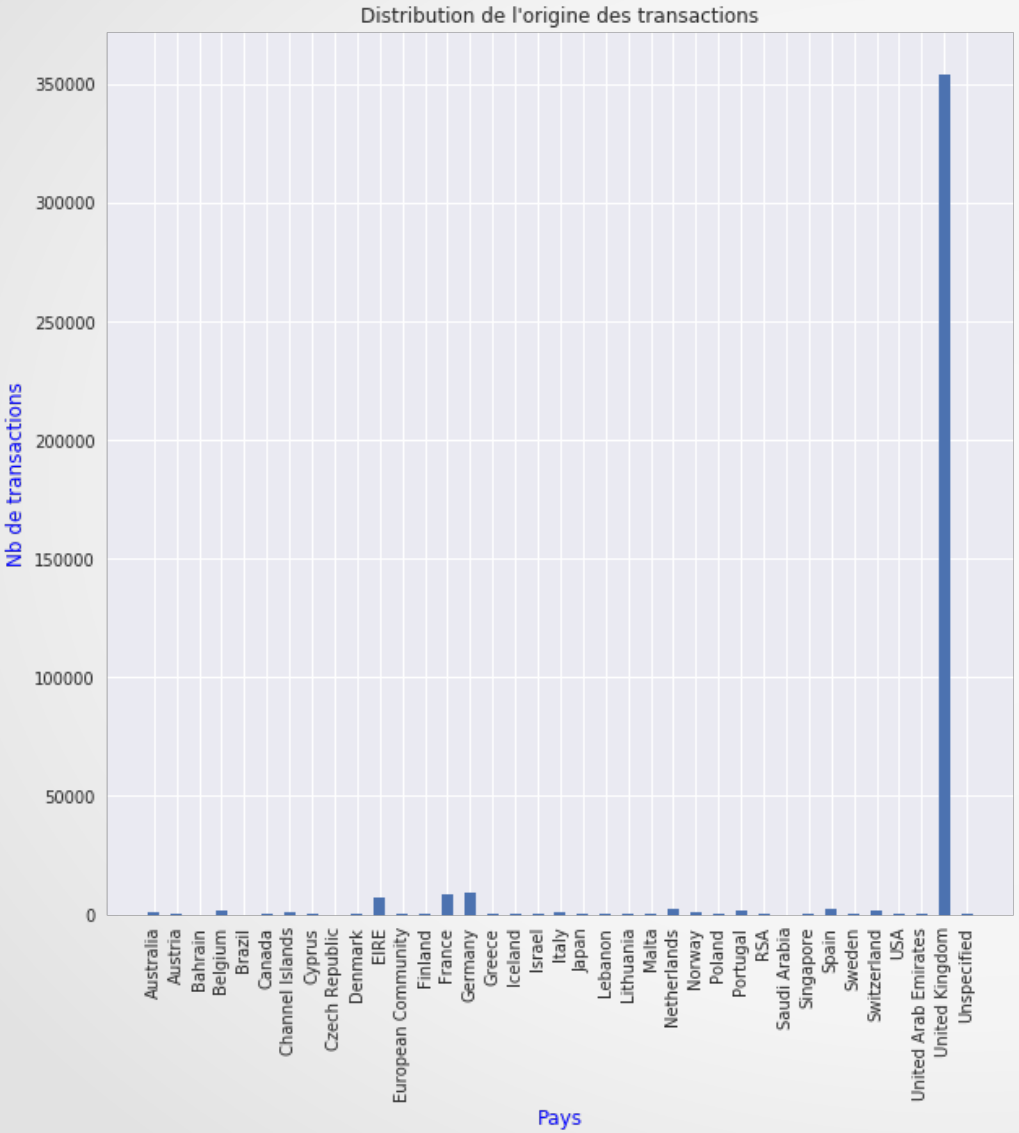


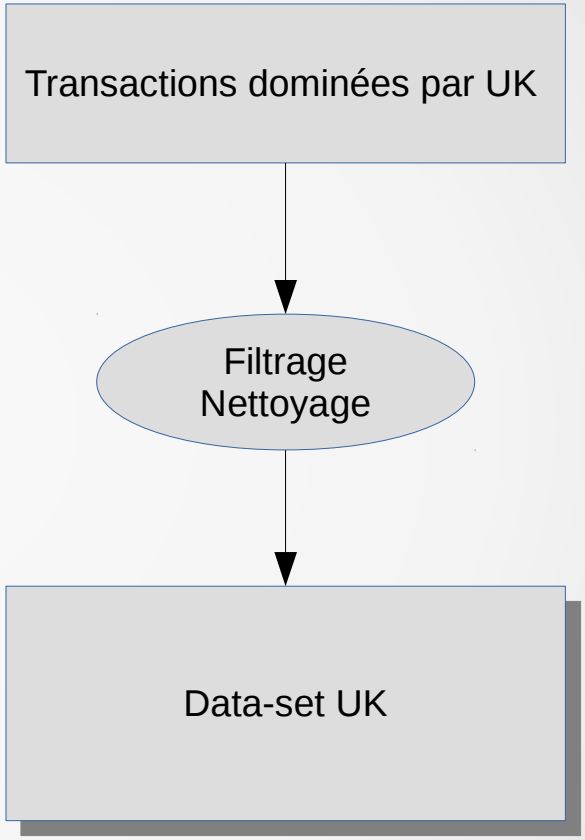


Préparation des données

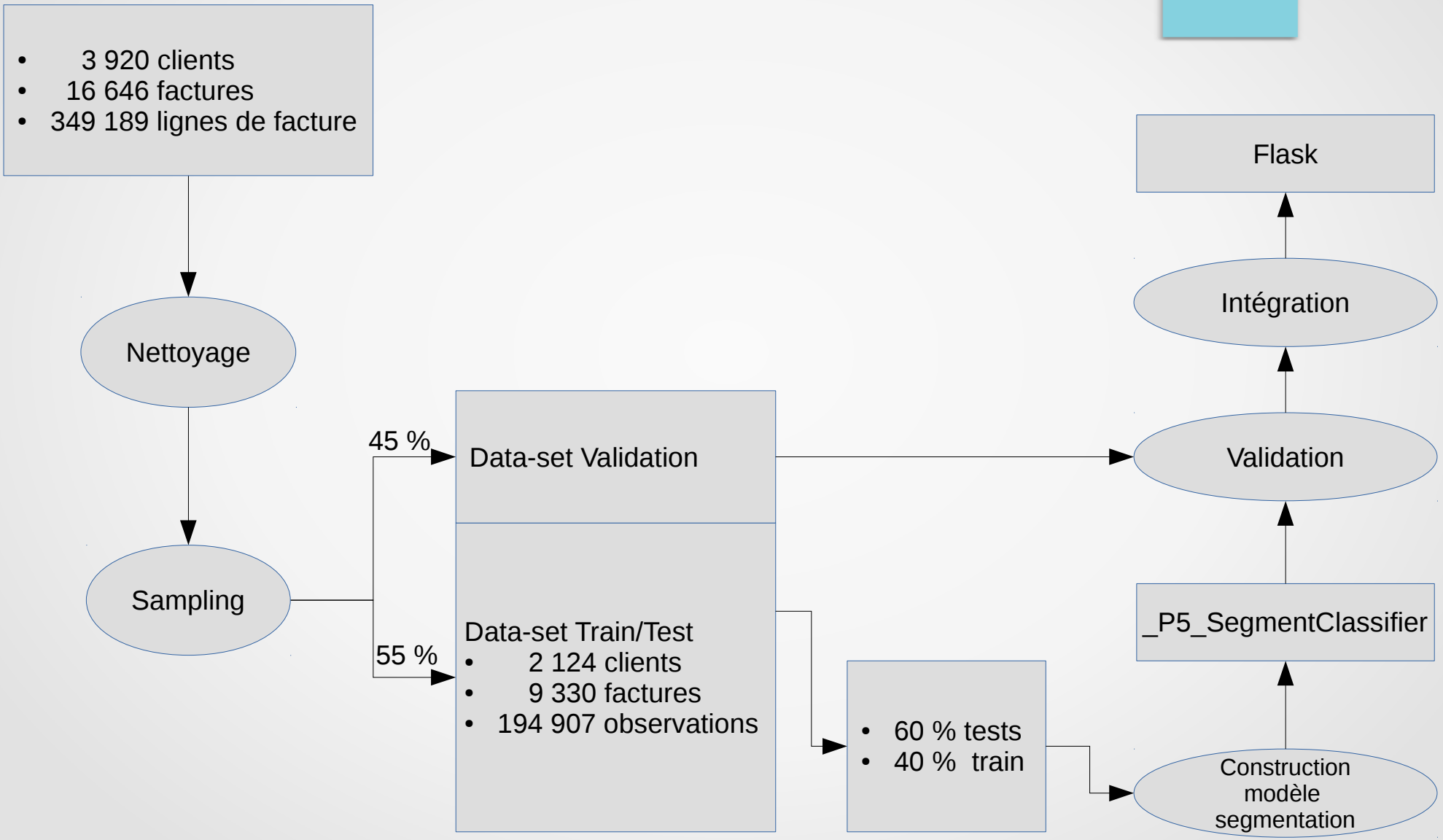


Exploration des données





Sampling


3 920 clients
16 646 factures
349 189 lignes de facture
Nettoyage
Sampling
45 %
55 %
Data-set Validation
Data-set Train/Test
2 124 clients
9 330 factures
194 907 observations
60 % tests
40 % train
Flask
Intégration
Validation
_P5_SegmentClassifier
Construction modèle segmentation

Analyse exploratoire : Activité = F(temps)

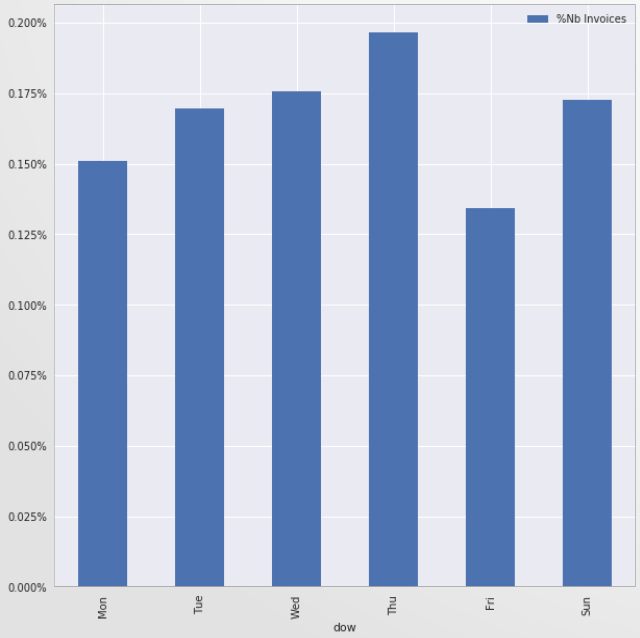
Facturation	
POD	
1	192 476
2	2 431

Yearly Facturation	
year	
2010	12 954
2011	181 953

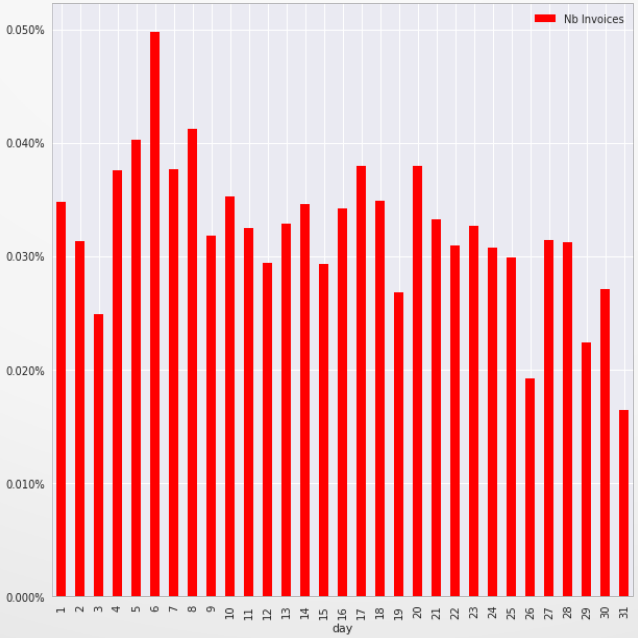
Period of day :
1 : 7:00 AM < Period <= 19:00 AM
2 : 19:00 PM < Period <= 07:00 AM

InvoiceDate

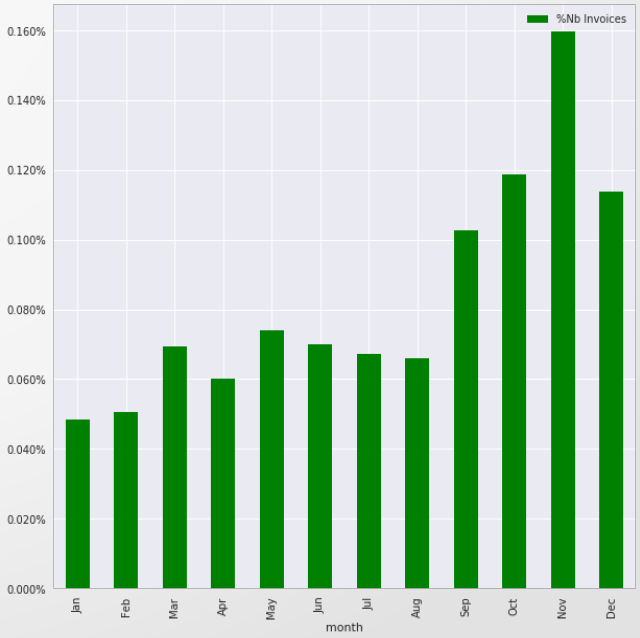
DOW



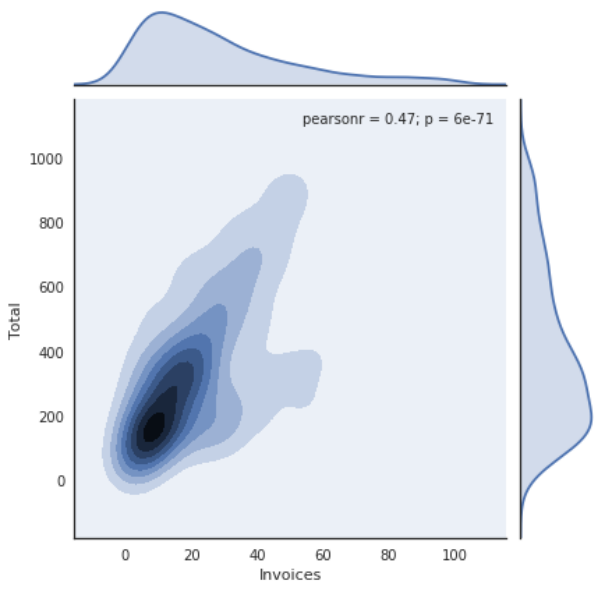
DOM

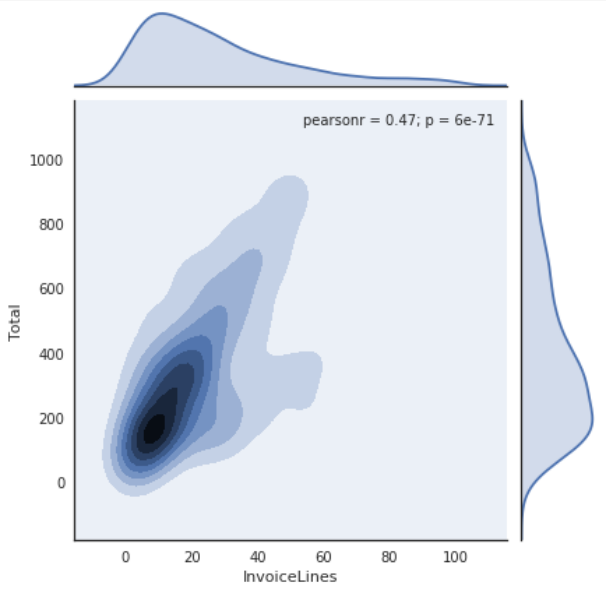


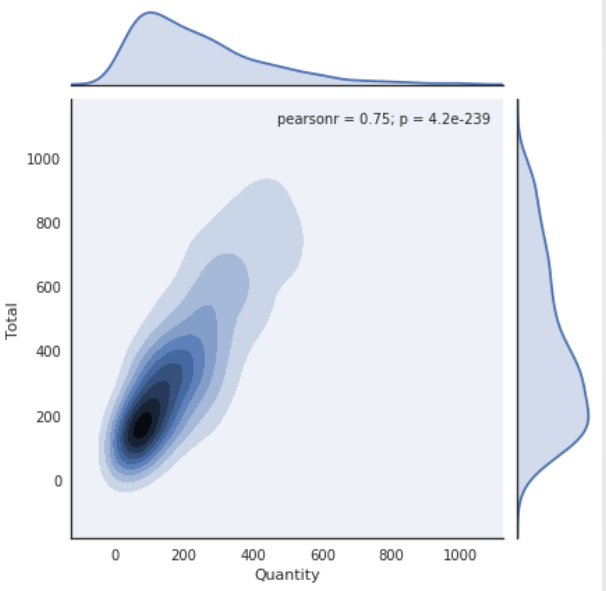
Month



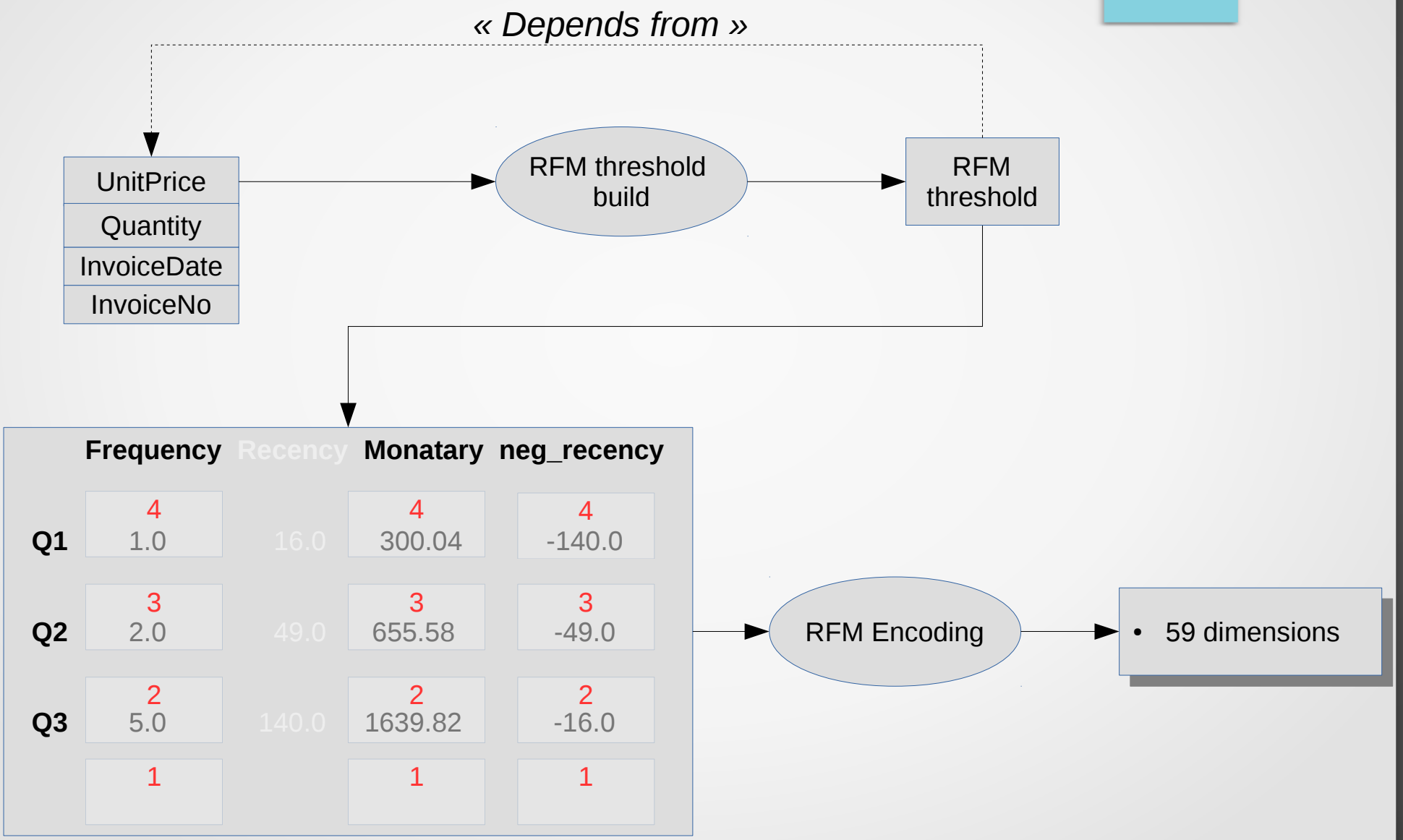
Analyse exploratoire : Revenus = F(features)



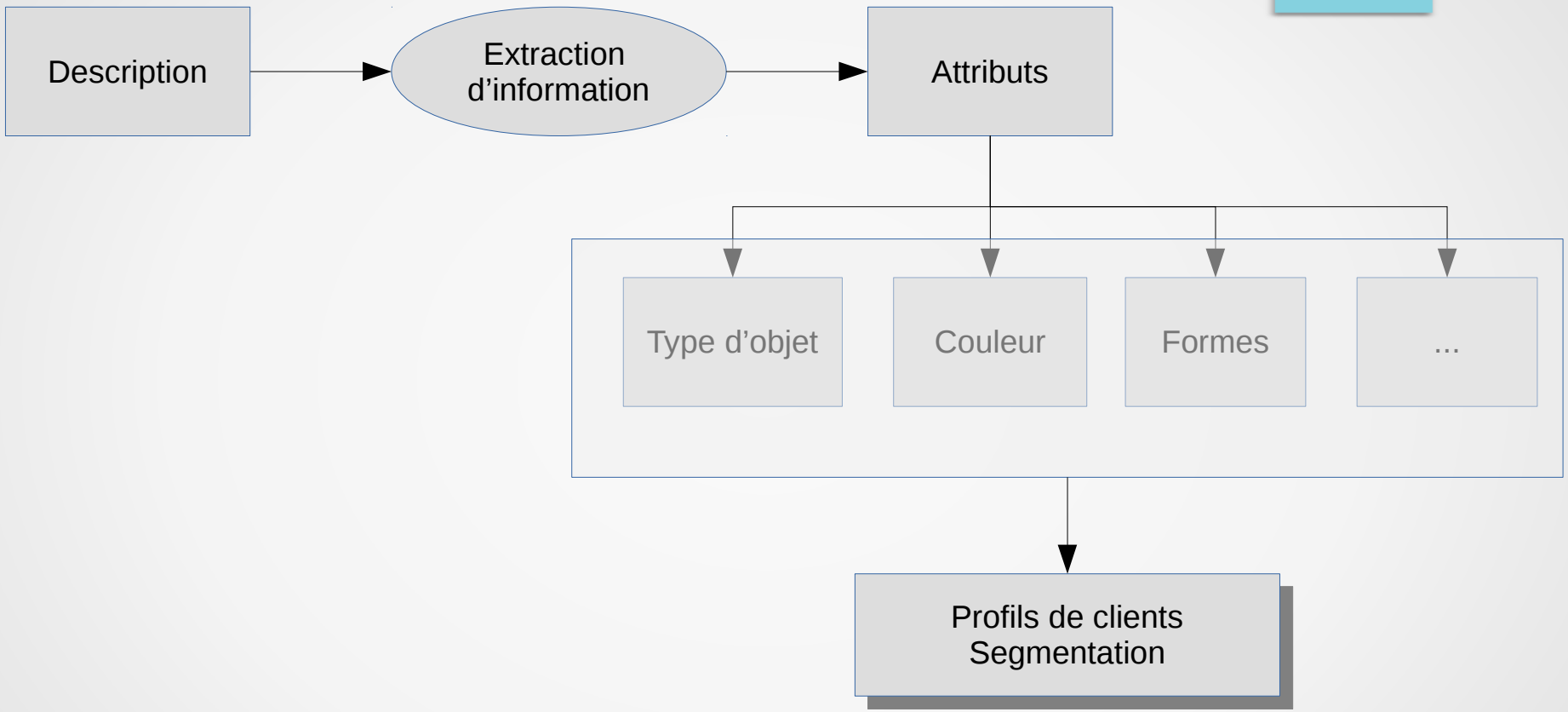




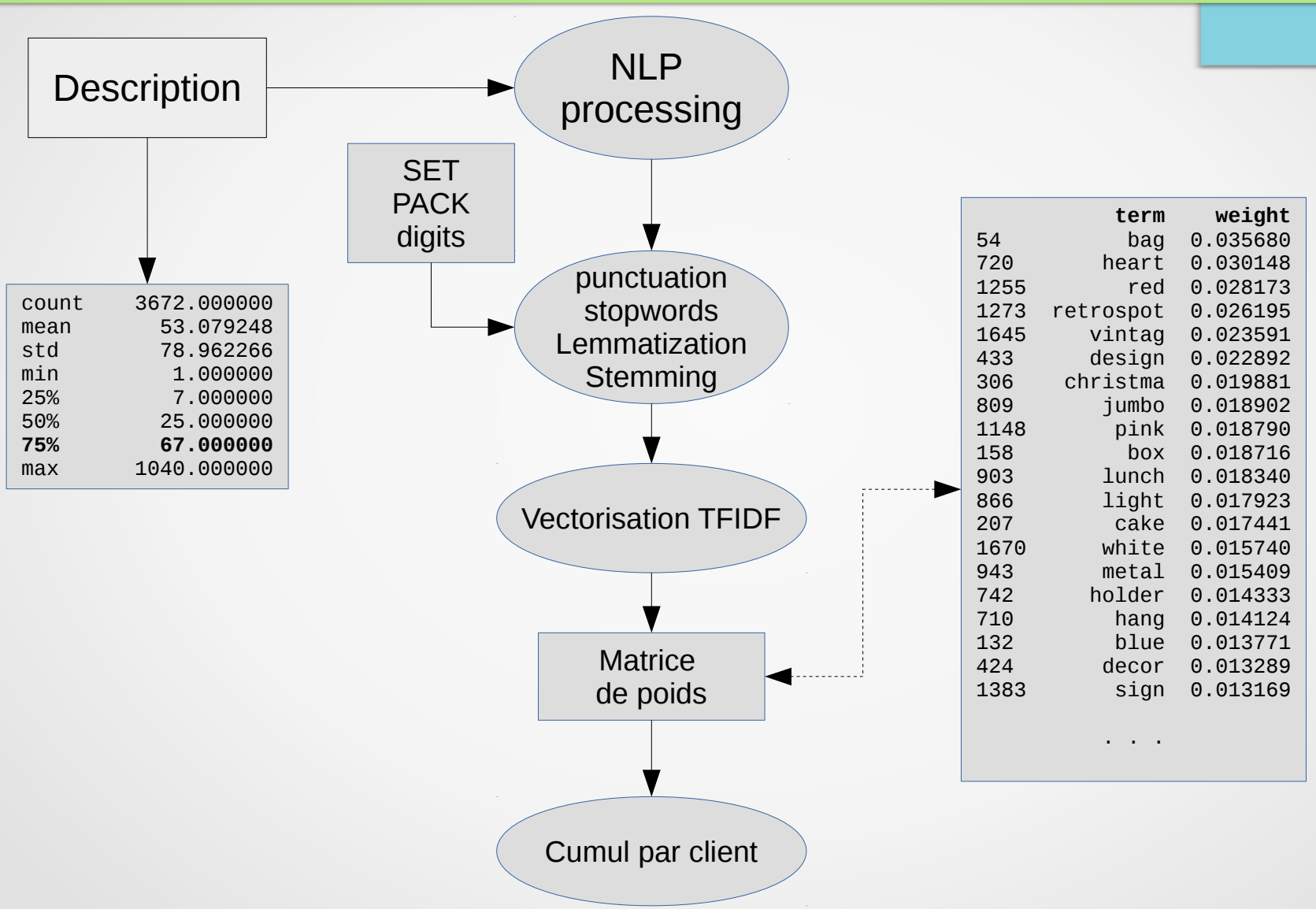
RFM : Traitement & durée de vie



Analyse exploratoire : Description



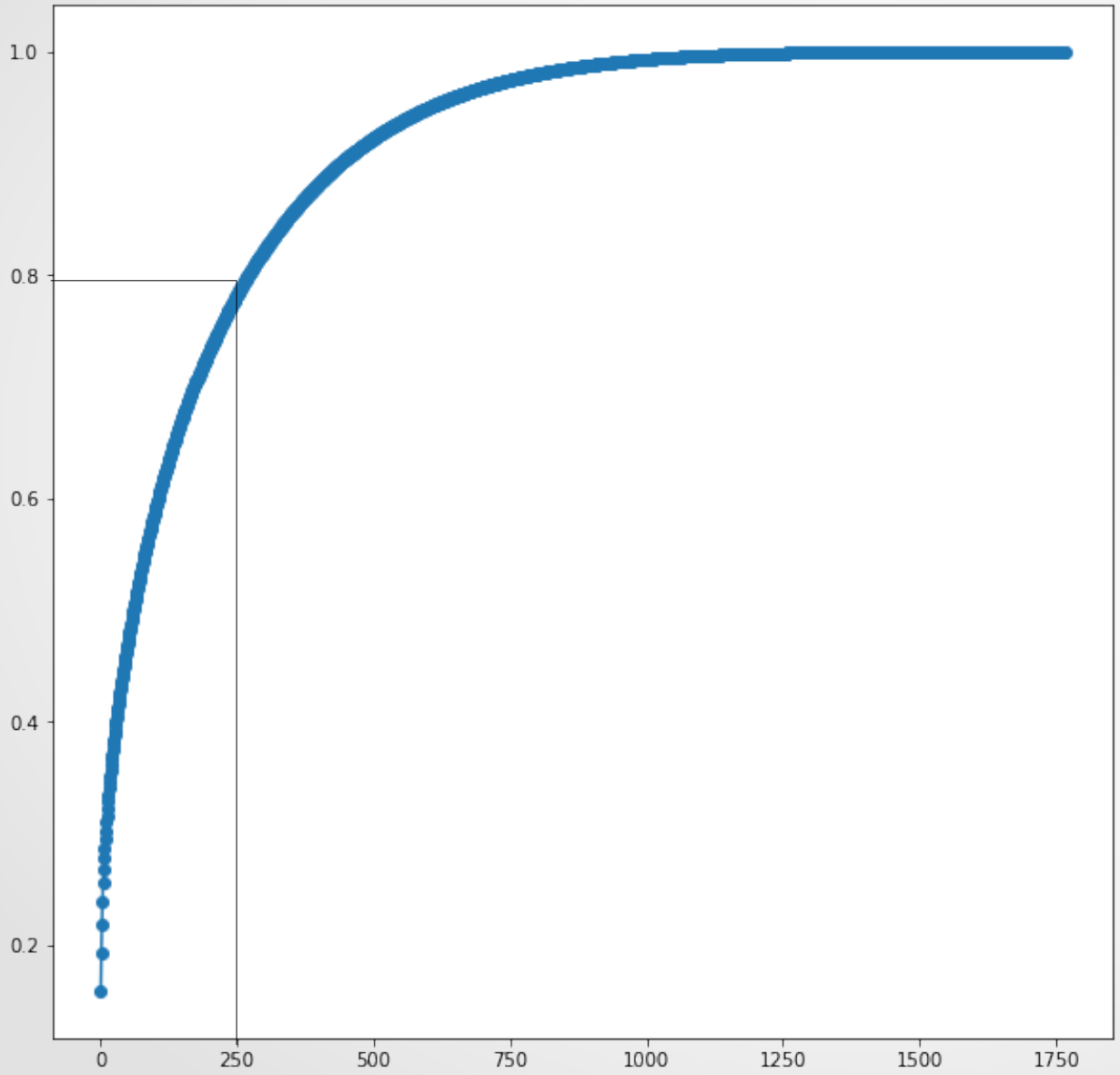
Analyse exploratoire : items



count	3672.000000
mean	53.079248
std	78.962266
min	1.000000
25%	7.000000
50%	25.000000
75%	**67.000000**
max	1040.000000

	term	weight
54	bag	0.035680
720	heart	0.030148
1255	red	0.028173
1273	retrospot	0.026195
1645	vintag	0.023591
433	design	0.022892
306	christma	0.019881
809	jumbo	0.018902
1148	pink	0.018790
158	box	0.018716
903	lunch	0.018340
866	light	0.017923
207	cake	0.017441
1670	white	0.015740
943	metal	0.015409
742	holder	0.014333
710	hang	0.014124
132	blue	0.013771
424	decor	0.013289
1383	sign	0.013169
	. . .	

Variables NLP : réduction de dimension

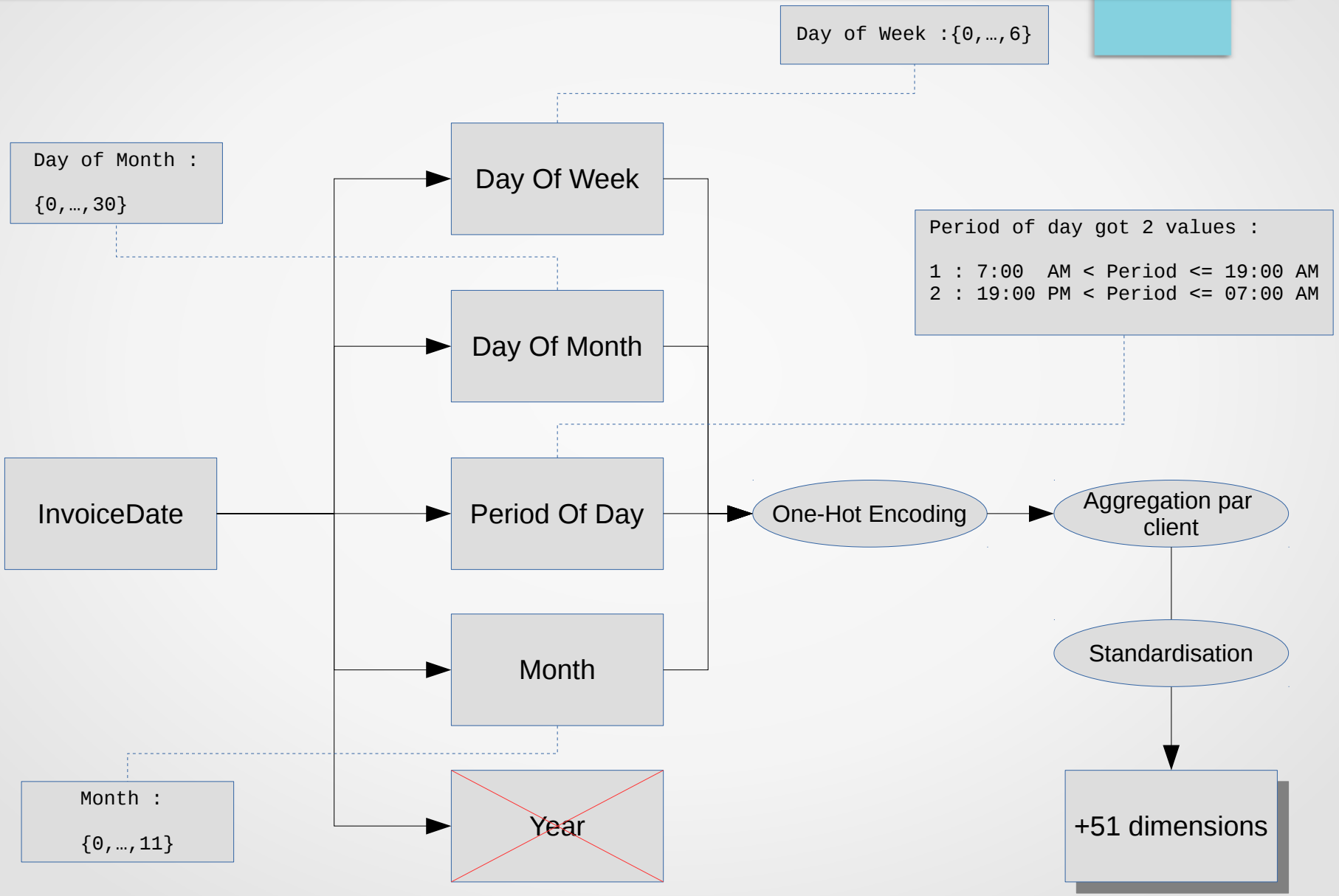


Traitement NLP : 1766 dimensions

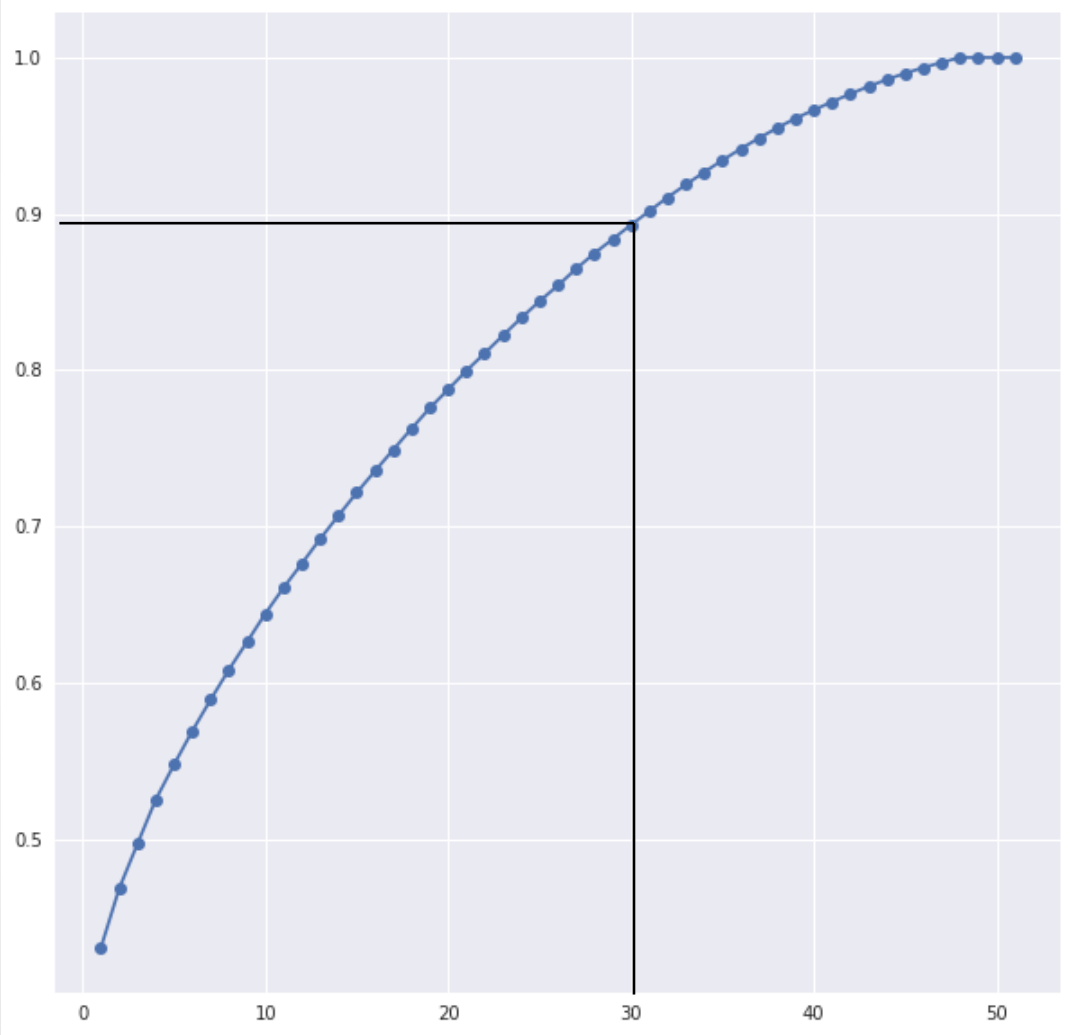
Hypothèse :
linéarité du phénomène

Nb dimensions :
250 ⇒ 80 % variance expliquée

Time : Nouvelles dimensions (2010,2011)



Time : réduction de dimension



Nb de dimensions réduites: 30

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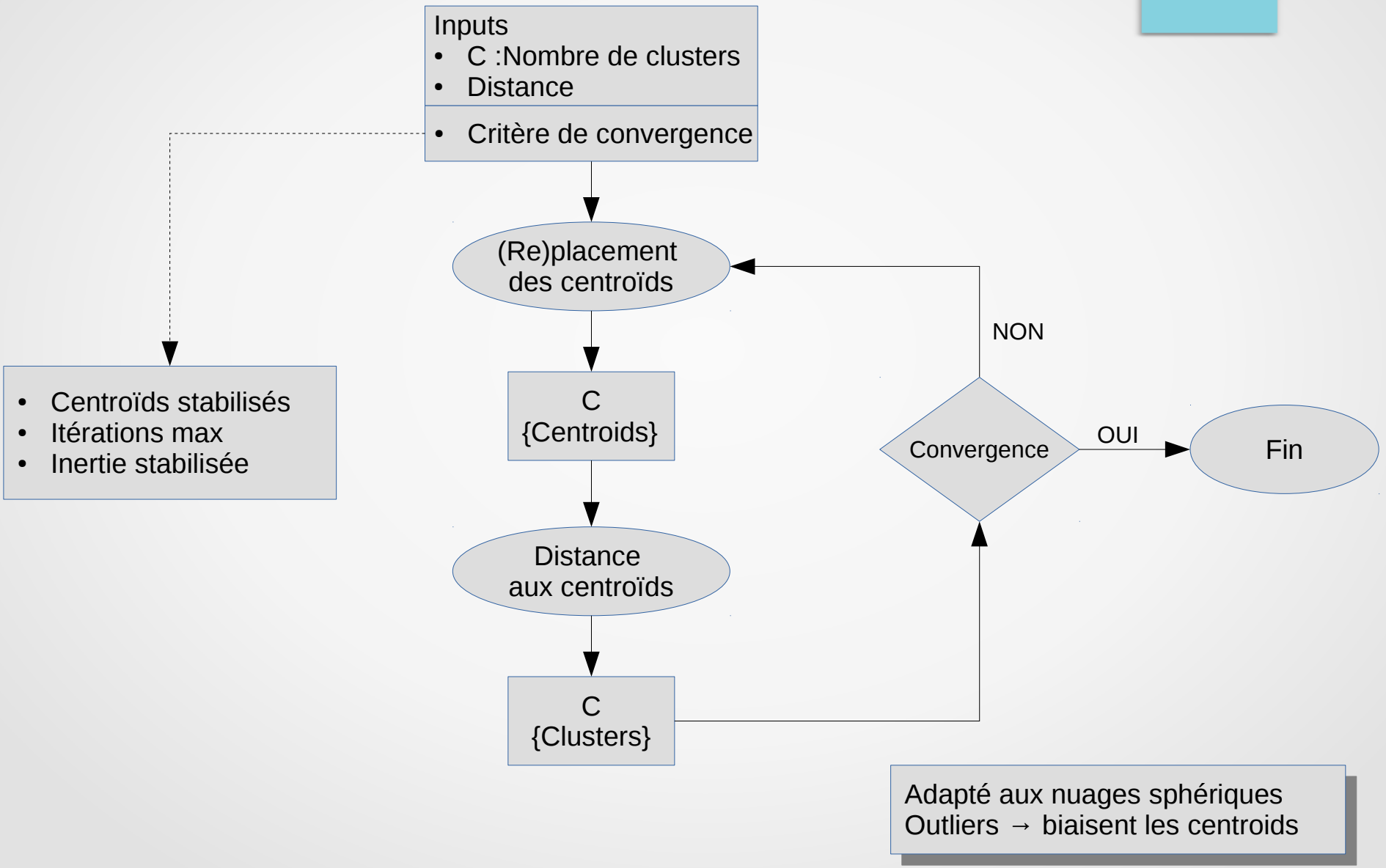
Clustering

- Kmeans
- GMM

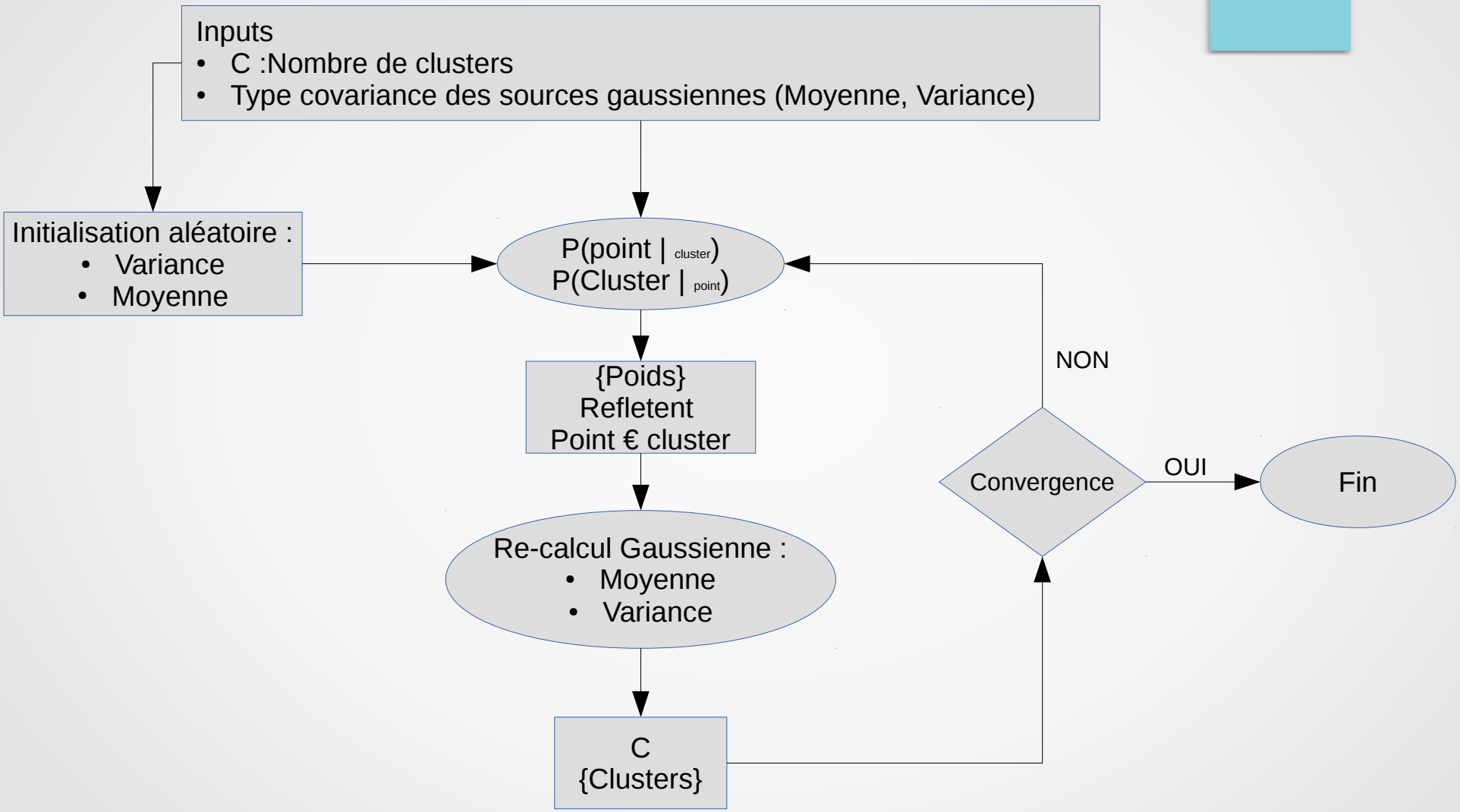
Data model :

- Complexity : 2 124
- Dimensions : 339

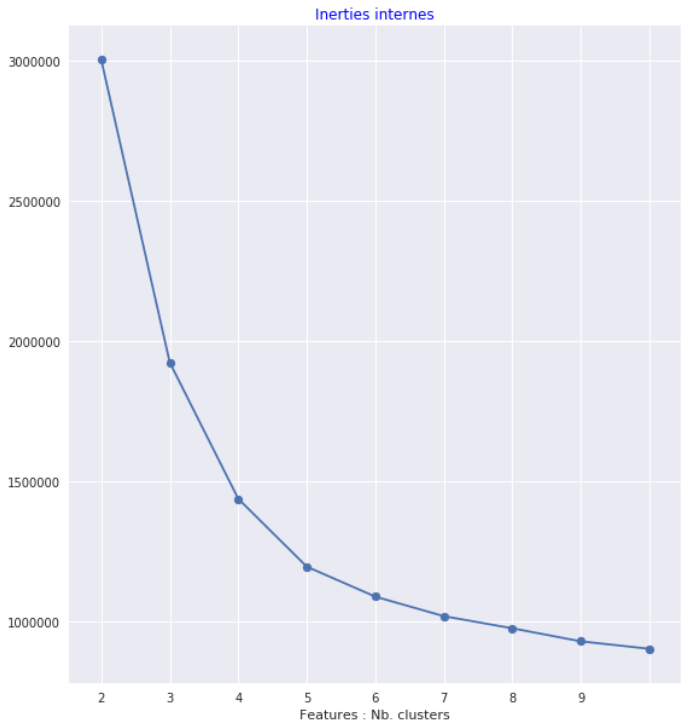
Kmeans : description

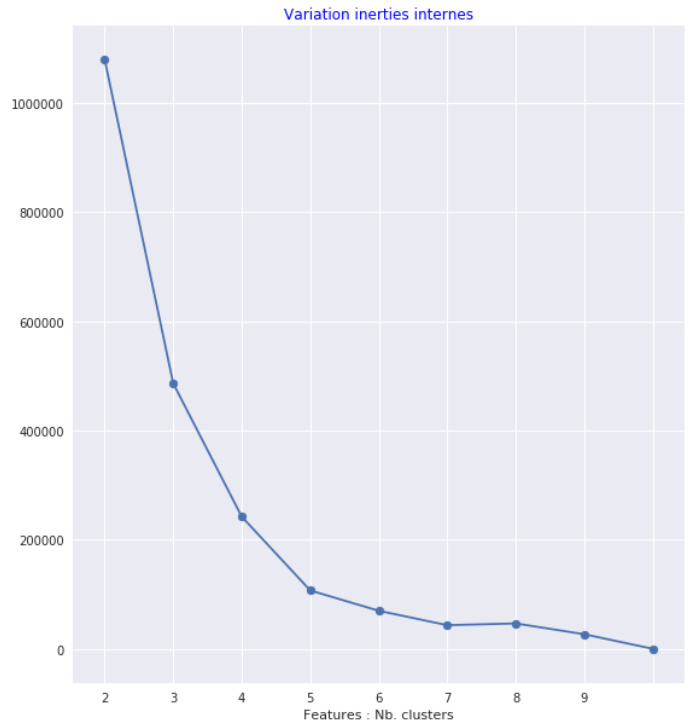


GMM: description

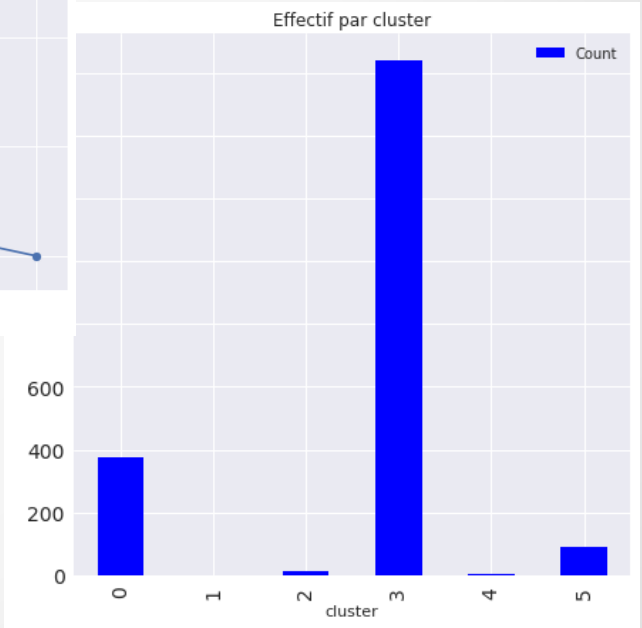


Kmeans : clustering vs intra-cluster inertias

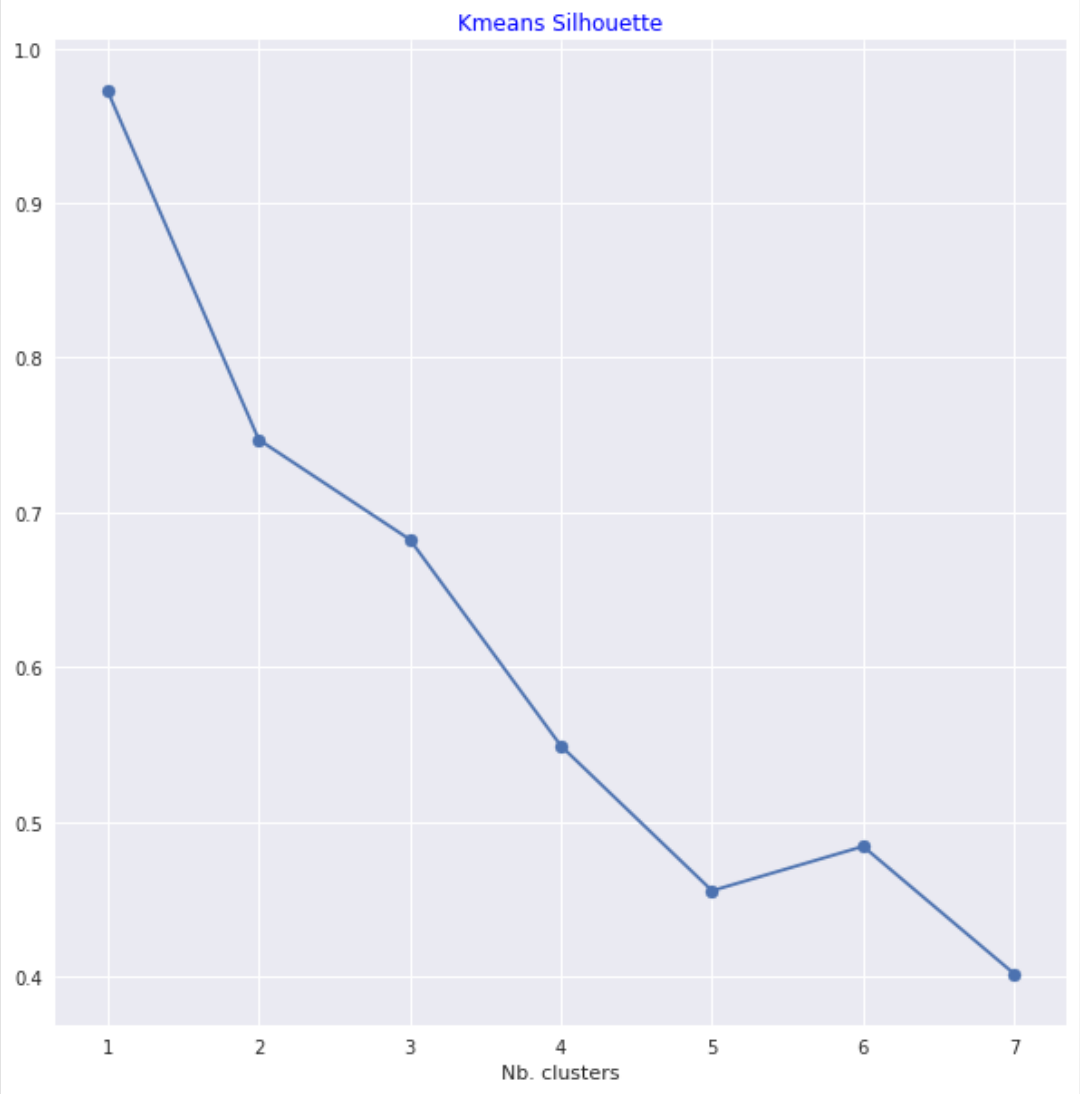


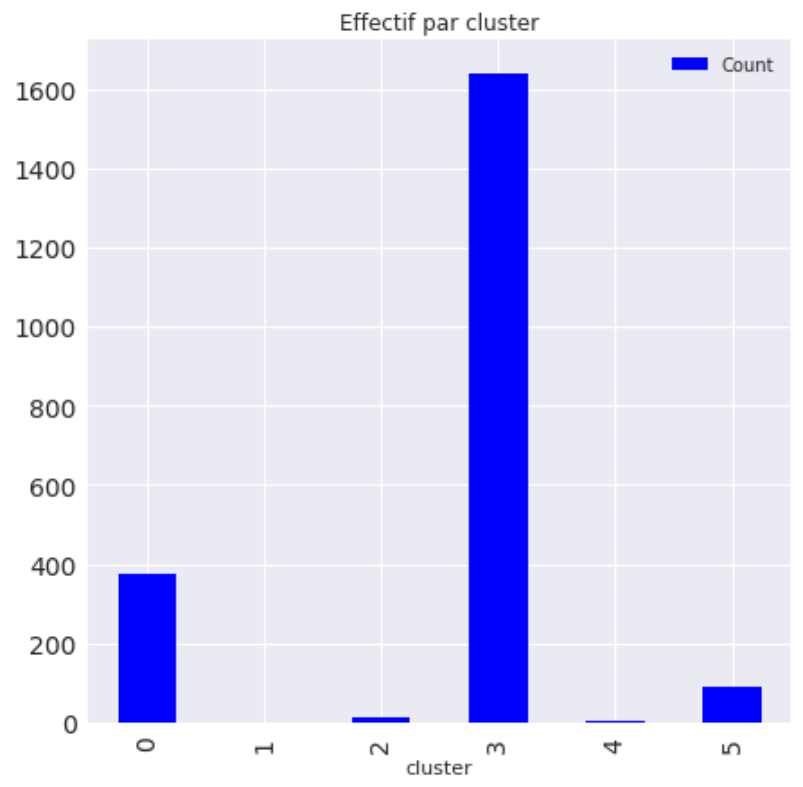


cluster	Count
0	377
1	1
2	11
3	1641
4	2
5	92



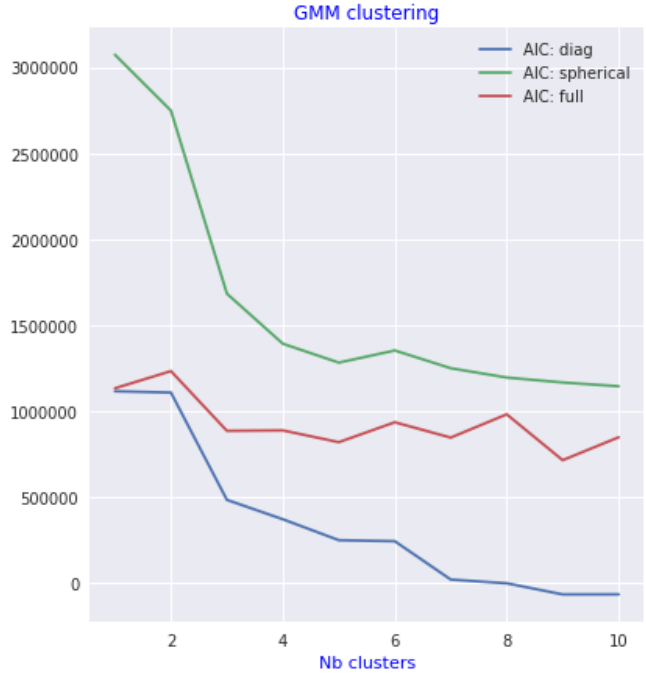
Kmeans : clustering vs Silhouette

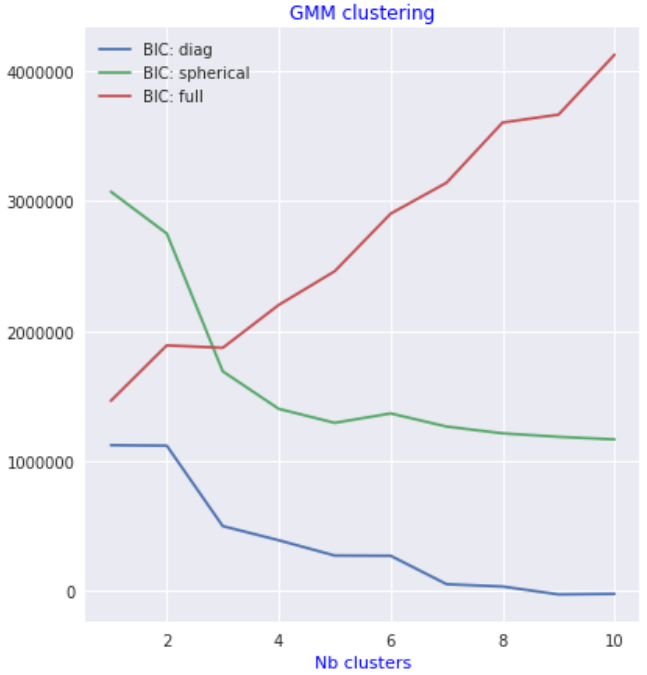




cluster	Count
0	377
1	1
2	11
3	1641
4	2
5	92

GMM clustering

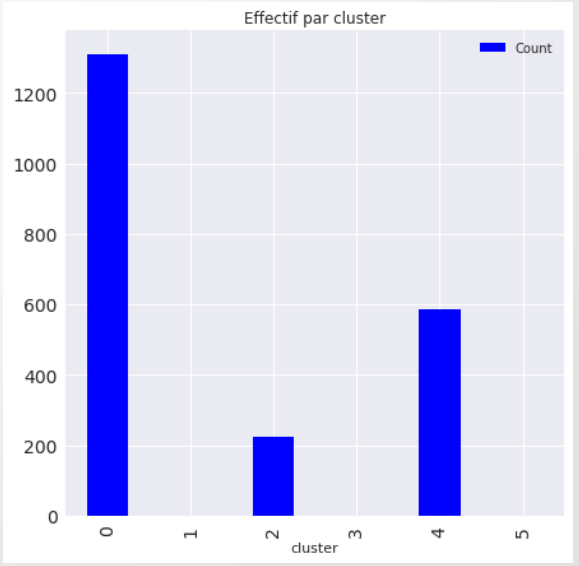




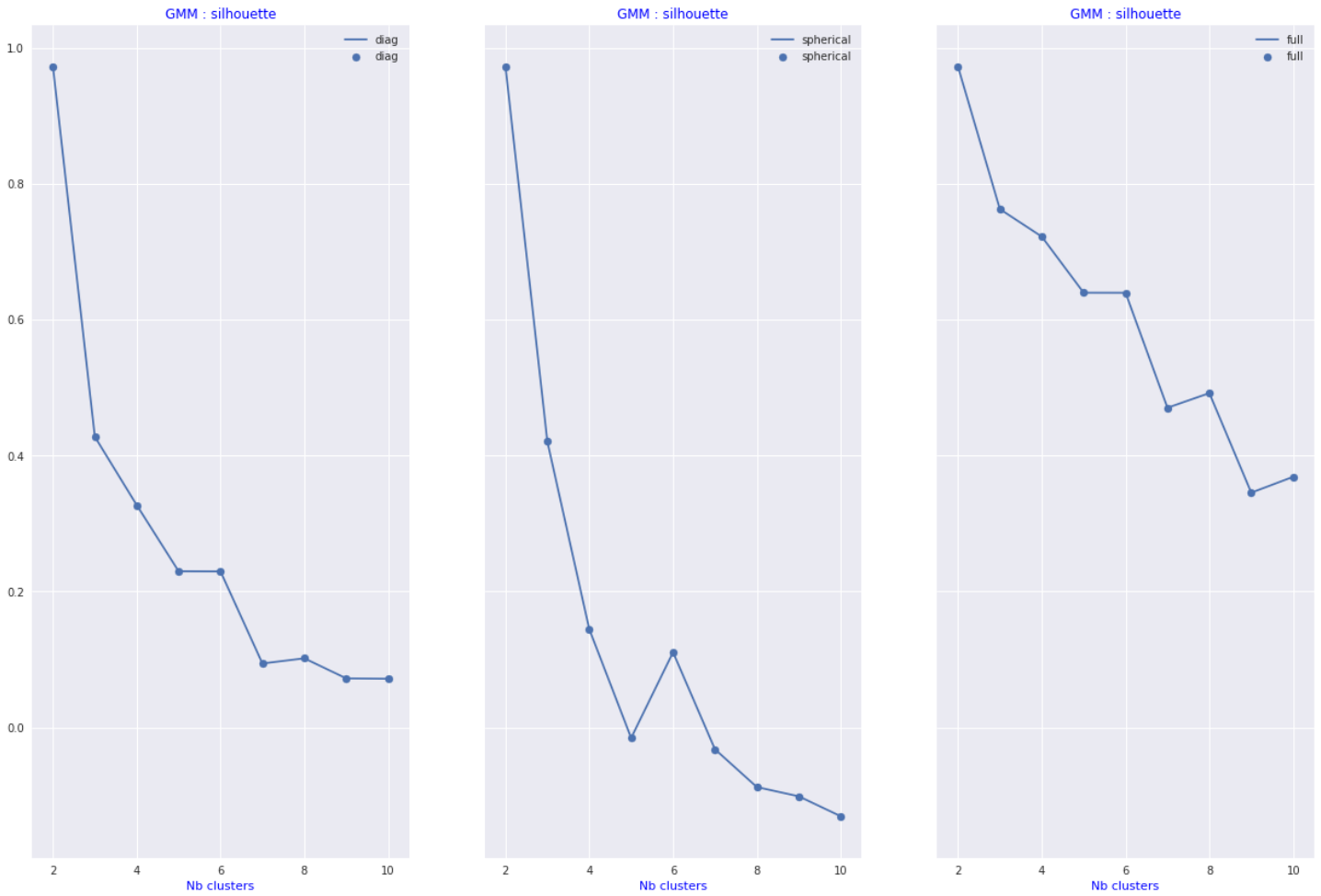
Nb optimal de clusters
Type de covariance :

- Sphérique : 3 clusters
- Diagonale : 3 clusters

cluster	Count
0	1312
1	1
2	224
3	1
4	585
5	1



GMM : silhouette vs covariance type



Nb optimal de clusters :

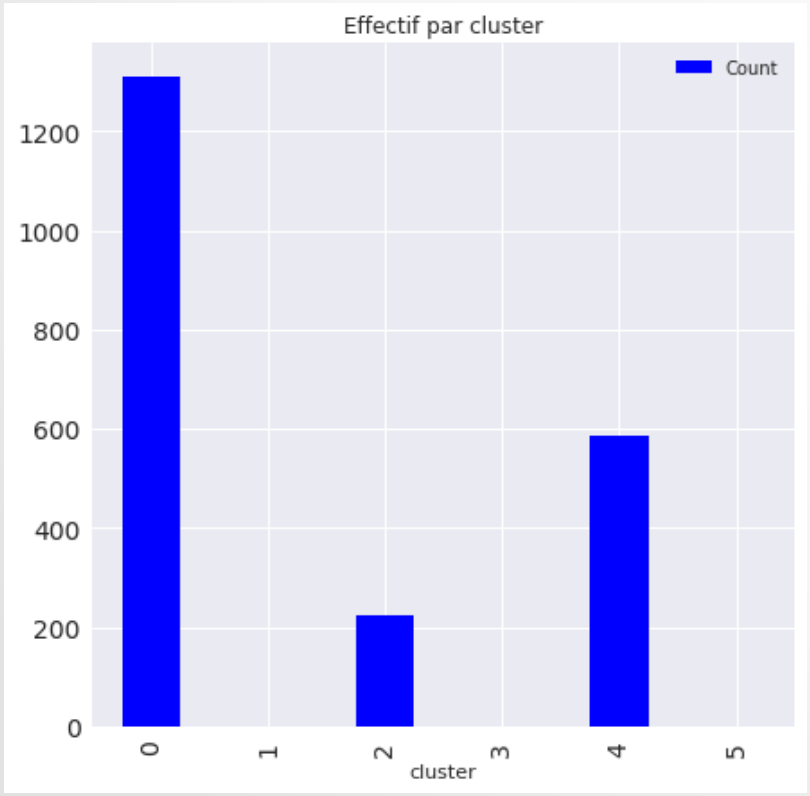
- Diagonale : 3 clusters
- Sphérique : 3 clusters
- Full : 3 clusters

Clustering : choix de l'algo & hyp. Param.

GMM

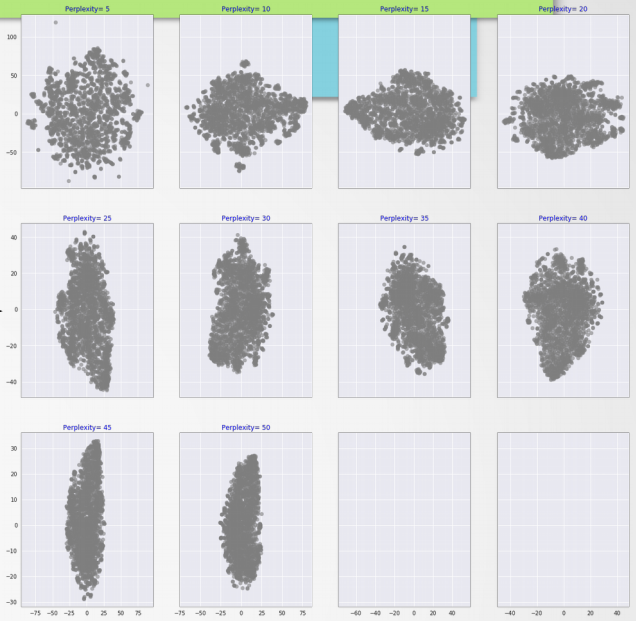
Type de covariance : Diagonale

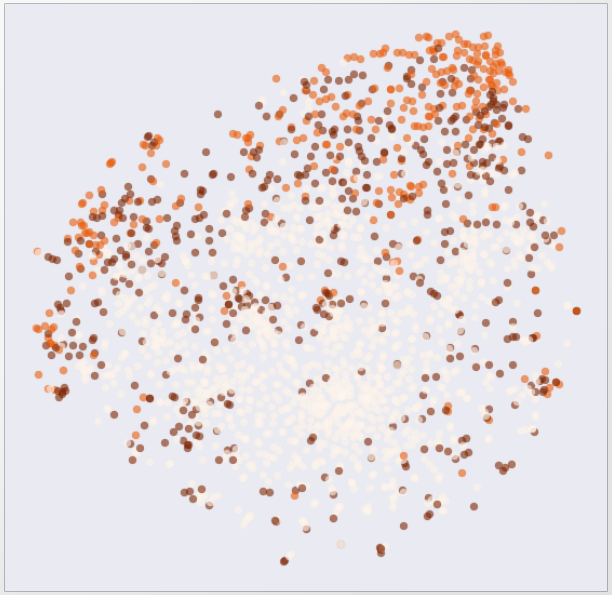
Nombre de clusters : 6 → 3 : 0, 2, 4



cluster	Count
0	1312
2	224
4	585

T-SNE 2D





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Analyse des segments de marché

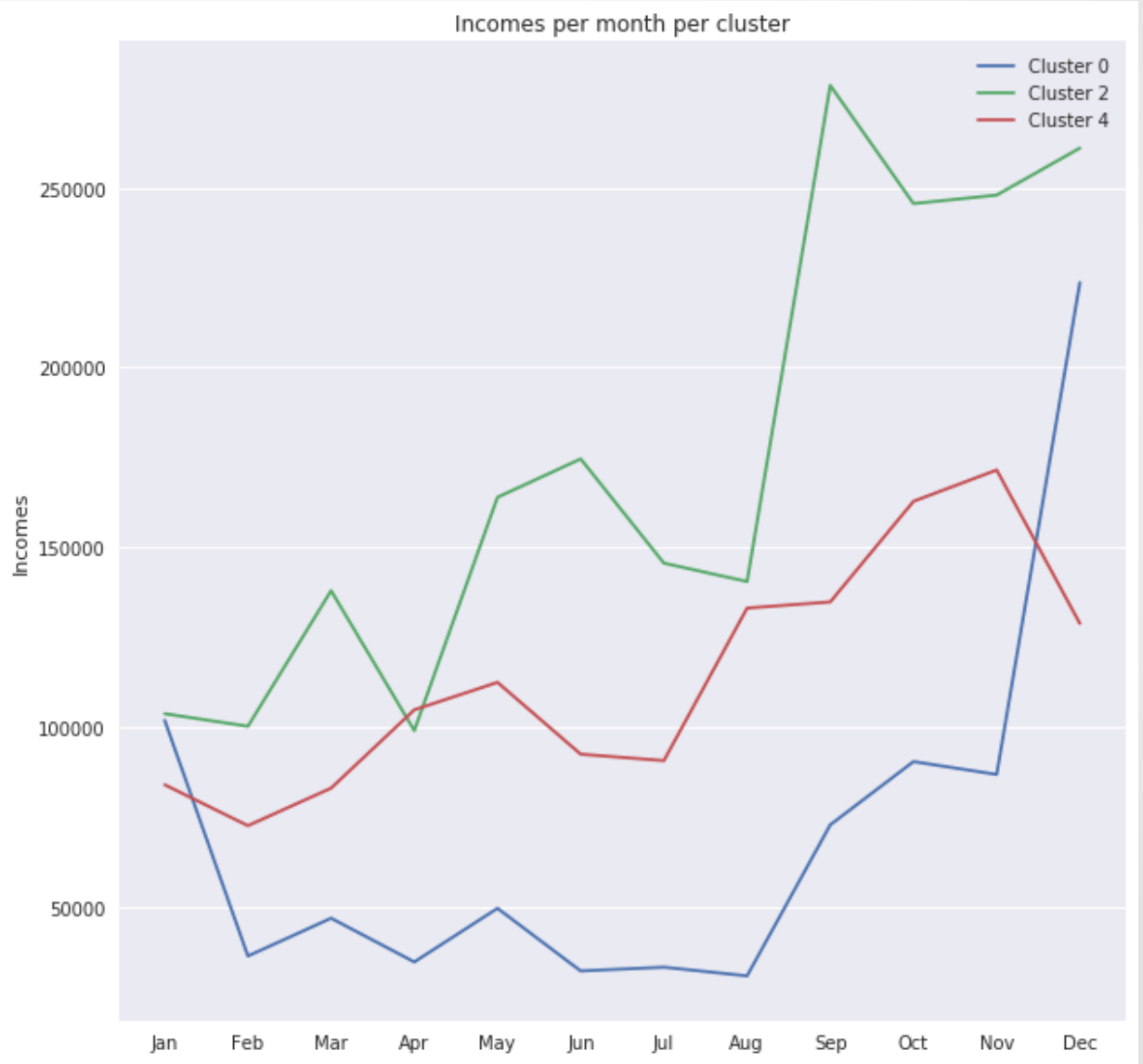
Market segments : Incomes

cluster	Count	%
0	1312	62
2	224	11
4	585	27

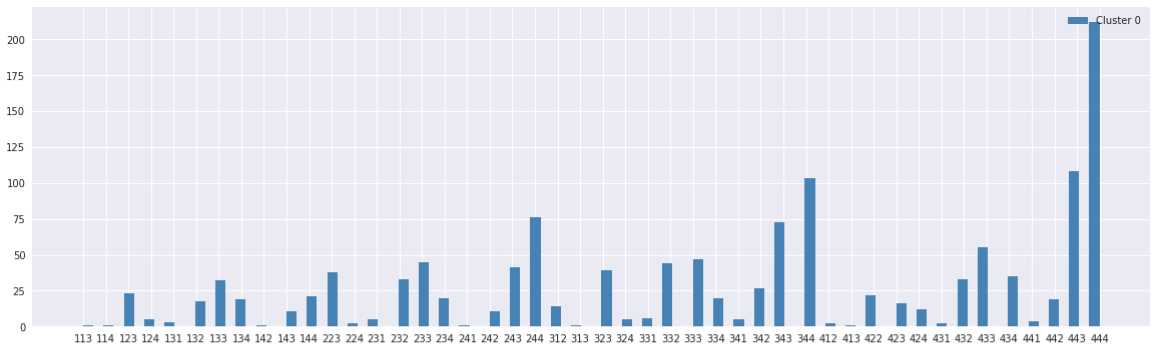
Segments 2 and 4 :

Feb → Jun : increases buy
Jul → Aug : decrease buy
Sep → Dec : high buy activity

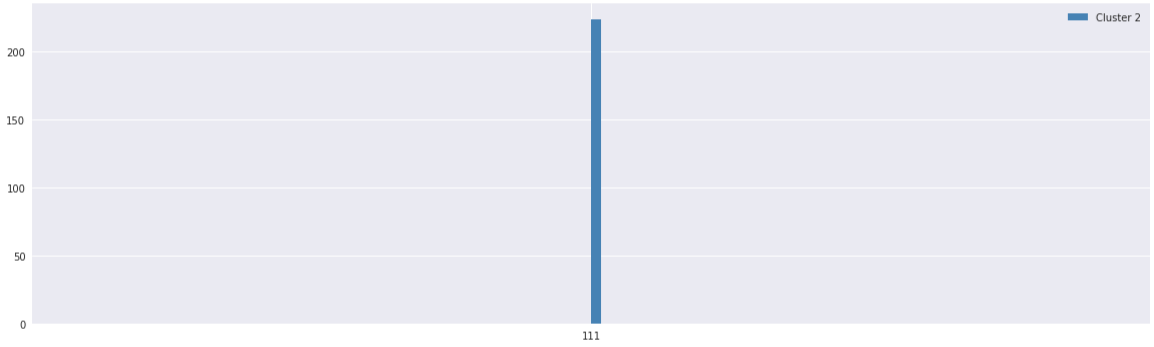
Segment 0 : Q3 increases buy



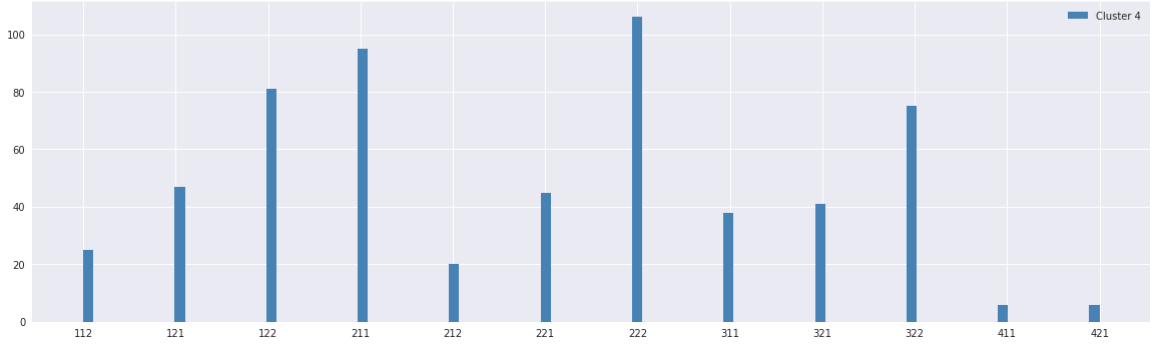
Markets segments: RFM distribution



Cluster 0 :
Week moneraty value
Low fidelity

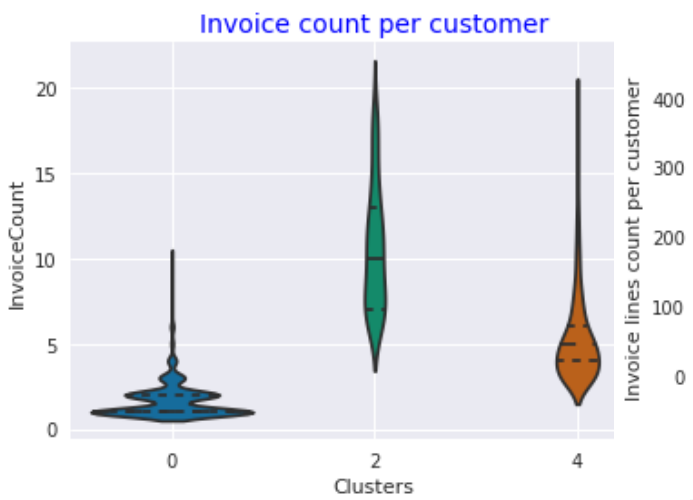


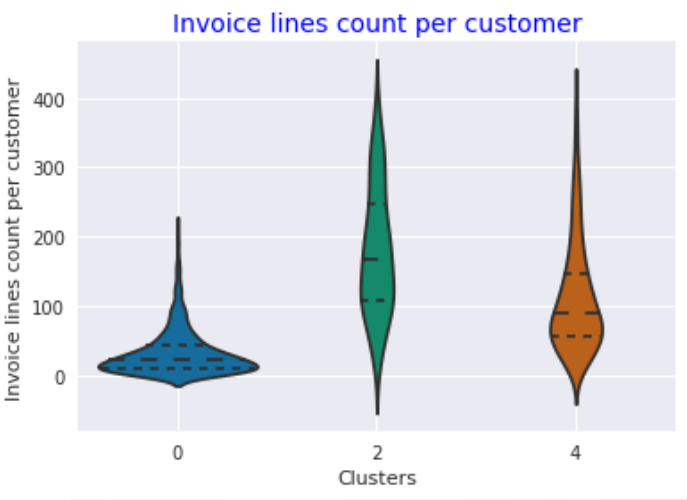
Cluster 2 :
High moneraty value
Buy often
High fidelity

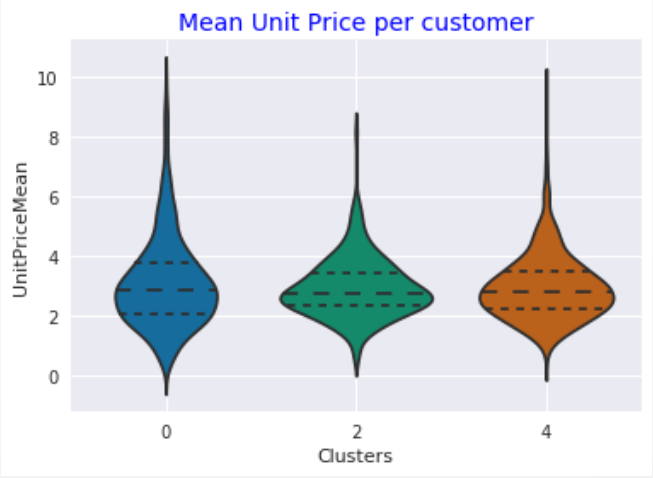


Cluster 4 :
Middle moneraty value
Buy often
Middle fidelity

Markets segments: behaviours (1)



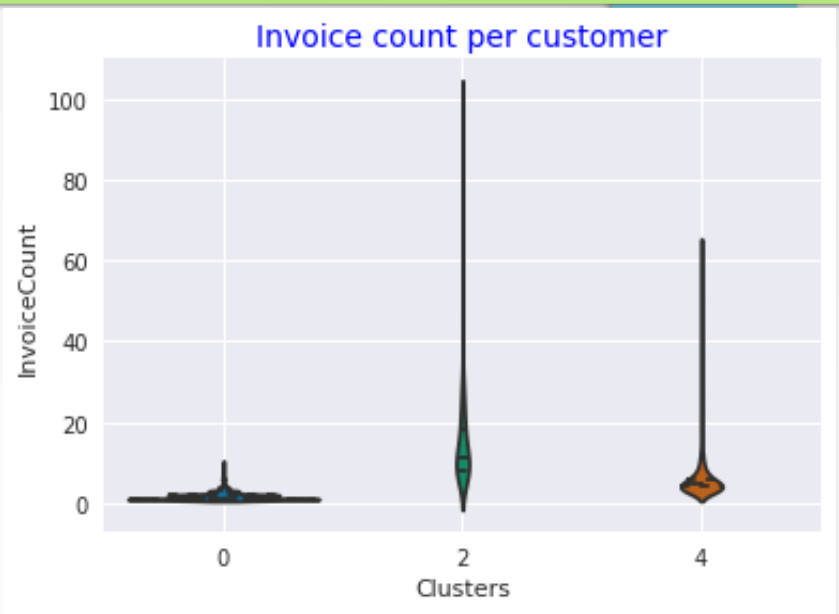


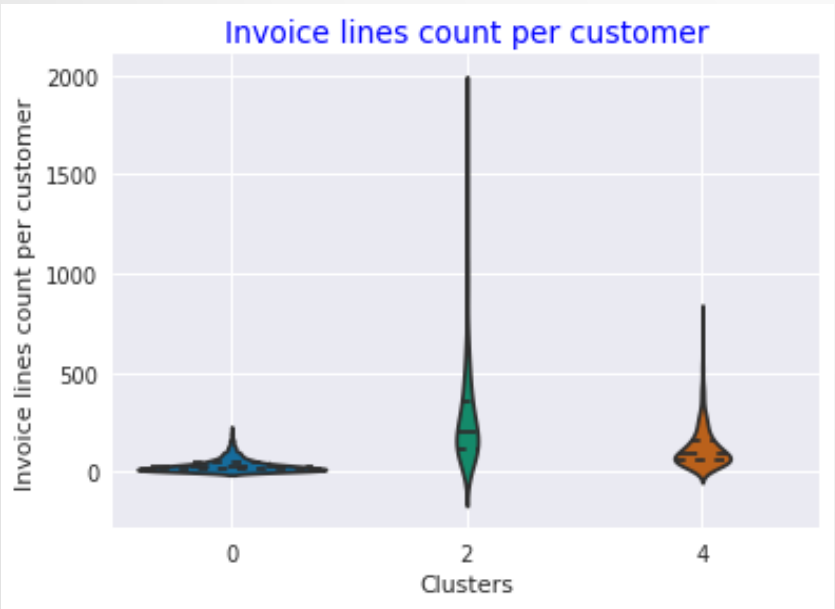


Clusters	Unique items	% items
0	3187	91 %
2	3098	88 %
4	3134	90 %

Chaque caractéristique possède une distribution associée à chaque segment.

Markets segments: behaviours (2)





Parcours Datascientist : projet 5

Prediction d’appartenance

- Random Forest
- SVC

Data model :

- Points: 2 124
- Dimensions : 339
- Variable cible : vecteur composé des valeurs des 3 classes

Random Forests: précision

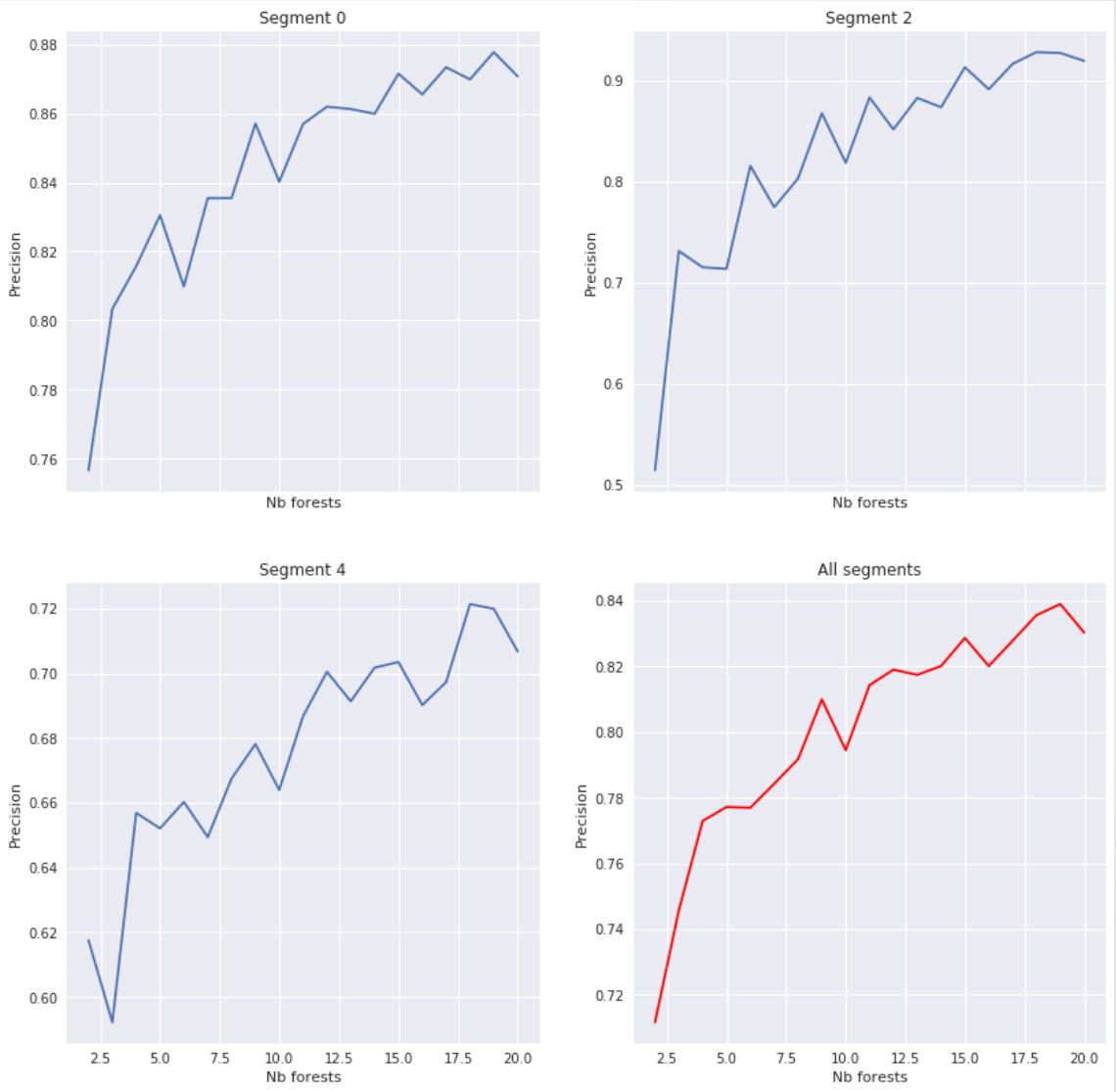
Nombre de répétitions : 10
Variation d'estimateurs: 1 à 20

19 Estimateurs

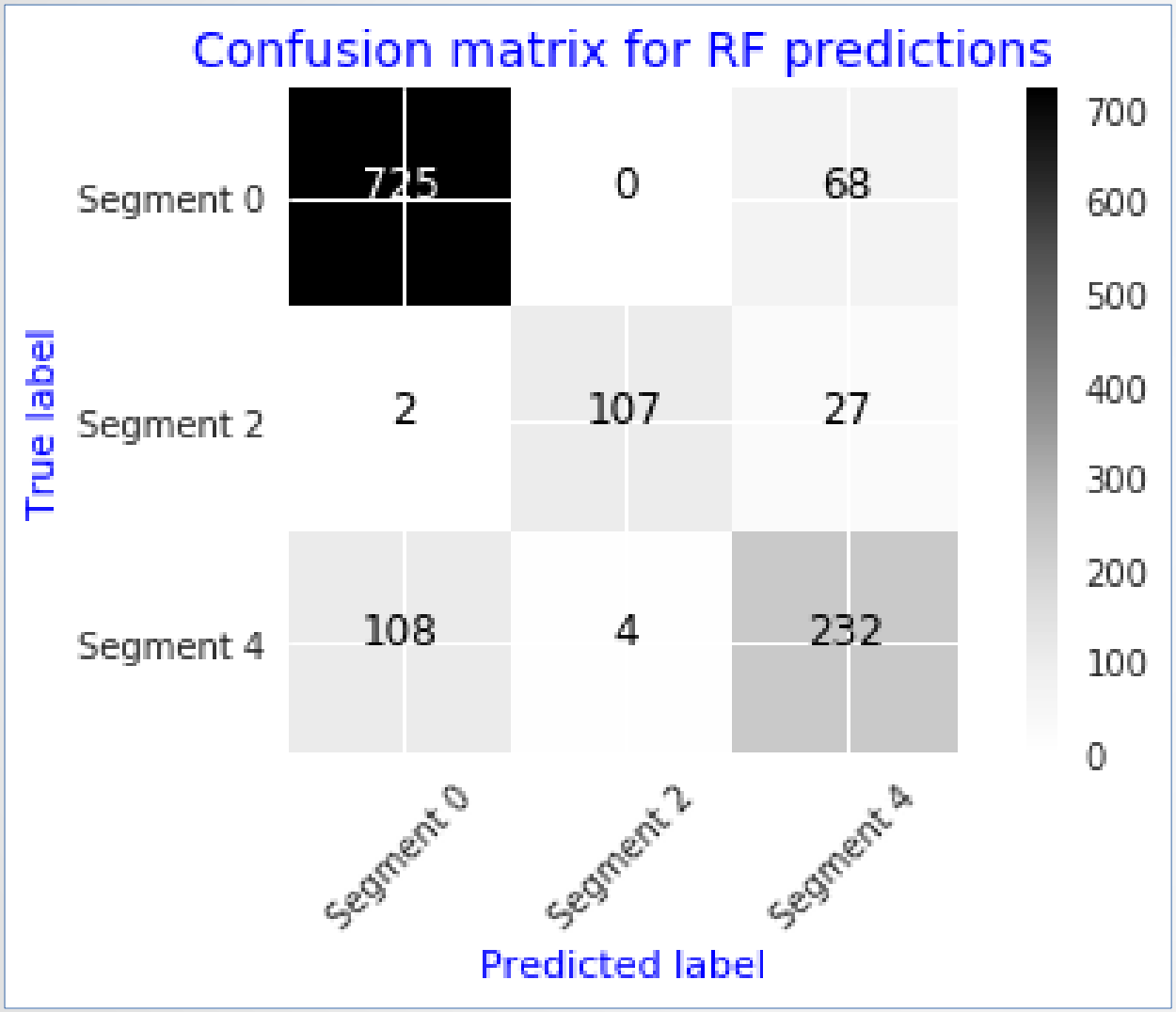
Répétitions : 10

Global accuracy = 0.84

Segment : 0 / : 0.87
Segment : 2 / : 0.93
Segment : 4 / : 0.72



Random Forests: matrice de confusion



	Segment 0	Segment 2	Segment 4
Précision	87 %	96 %	70 %
Recall	91 %	79 %	67 %
Spécificité	84 %	97 %	88 %
F-mesure	89 %	86 %	69 %

Random Forests: description

Selection aléatoire de features

Bootstrap

Overfitting

Echantillons aléatoires

Arbres de décision

Data-set

	Feature1	Feature2	Feature K	Labels
Obs 1	V1.1		Vk.1	0
Obs 2	V1.2		Vk.2	2
				0
				4
				2
Obs N	V1.N		Vk.N	4

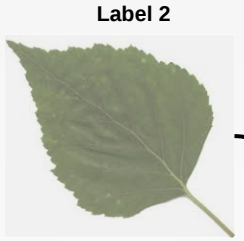
	Feature1	Feature2	Feature J	Labels
Obs 1	V1.1		Vj.1	0
Obs N	V1.N		Vj.N	4

	Feature1	Feature4	Feature J	Labels
Obs 1	V1.1		Vj.1	0
Obs N	V1.N		jk.N	4

	Feature1	Feature9	Feature J	Labels
Obs 1	V1.1		Vm.1	0
Obs N	V1.N		Vm.N	4

Random Forests: arbre de décision

	Feature1	Feature2	Feature K	Labels
Obs 1	V1.1		Vk.1	0
Obs 2	V1.2		Vk.2	2
				0
				4
				2
Obs N	V1.N		Vk.N	4



Feature J

Feature 2	Labels		
V2.1	0	2	4
	N1	N2	0

Feature 2	Labels		
V2.2	0	2	4
	0	N2	0

Feature 2	Labels		
V2.3	0	2	4
	N1	0	N3

V2.1 V2.2 V2.3

Feature 2

Feature 1	Labels		
V1.1	0	2	4
	N	0	0

Feature 1	Labels		
V1.2	0	2	4
	N1	N2	0

V1.1 V1.2

Feature 1

Noeud :
*** Index impureté de GINI**
*** Entropie**
*** Indice d'erreur**

Estimateur: SVC

Noyaux :

- Linéaire
- RBF
- Poly
- Sigmoid

LinearSVC

?

SVC : One vs Rest

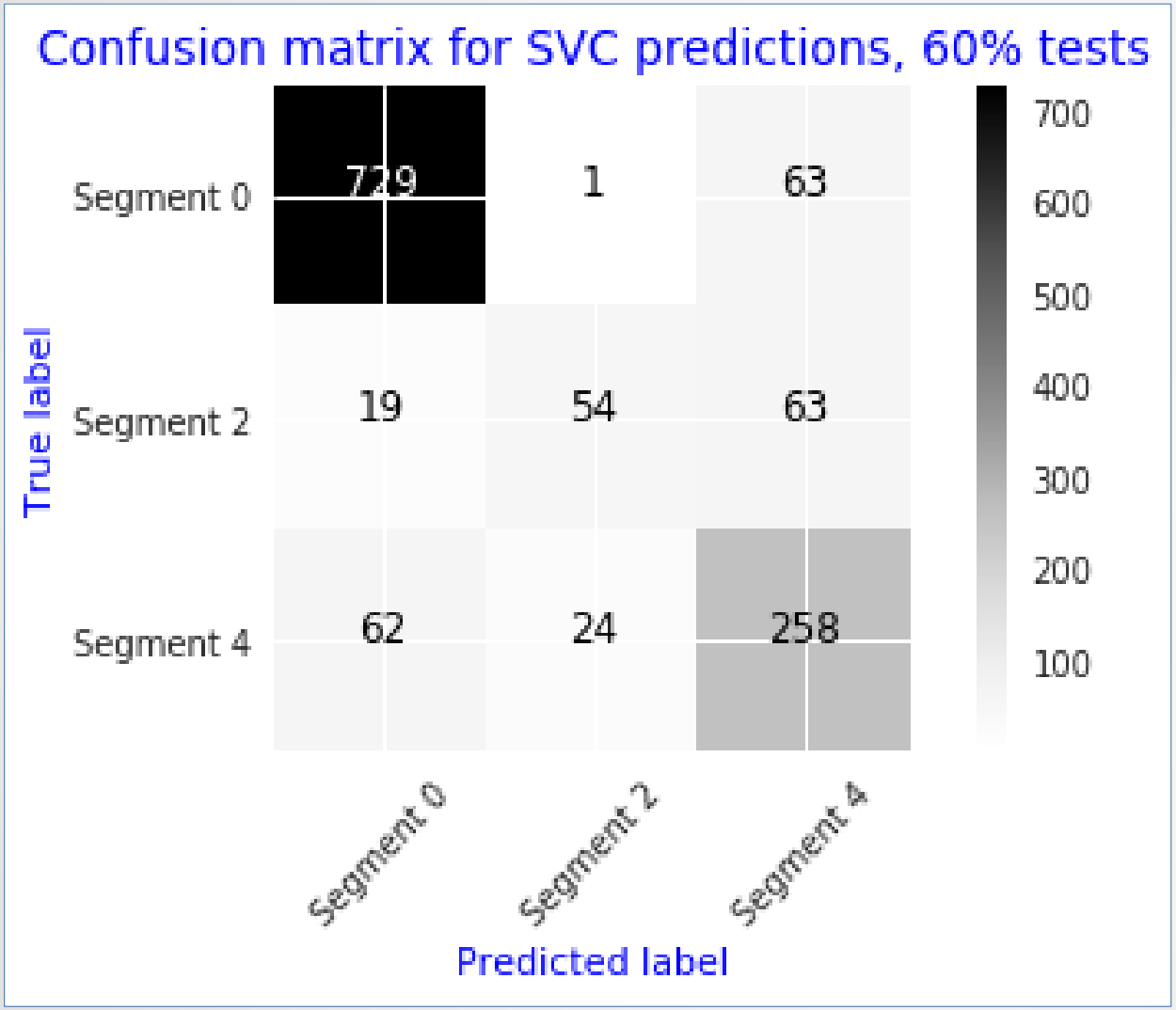
kernel= linear
Accuracy / segment : {0: 0.88, 2: 0.73, 4:0.70}
Global accuracy : 0.82

kernel= rbf
Accuracy / segment : {0: 0.83, 2: 0.73, 4 : 0.61}
Global accuracy : 0.77

kernel= poly
Accuracy / segment : {0: 0.70, 2: 0.66, 4 : 0.54}
Global accuracy : 0.68

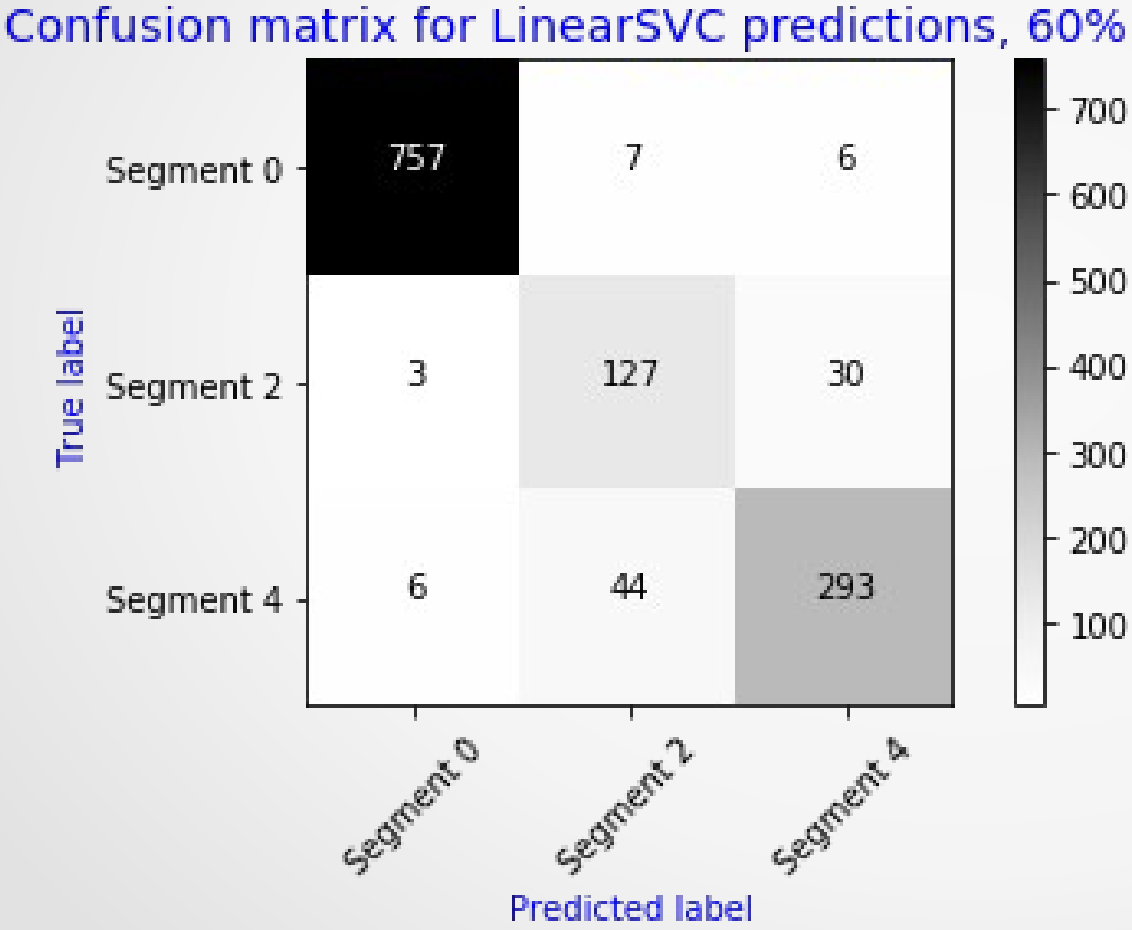
kernel= sigmoid
Accuracy / segment : {0: 0.79, 2: 0.27, 4:0.61}
Global accuracy : 0.66

SVC: matrice de confusion



	Segment 0	Segment 2	Segment 4
Précision	90 %	68 %	75 %
Recall	92 %	39 %	67 %
Spécificité	86 %	93 %	86 %
F-mesure	91 %	50 %	71 %

LinearSVC: matrice de confusion



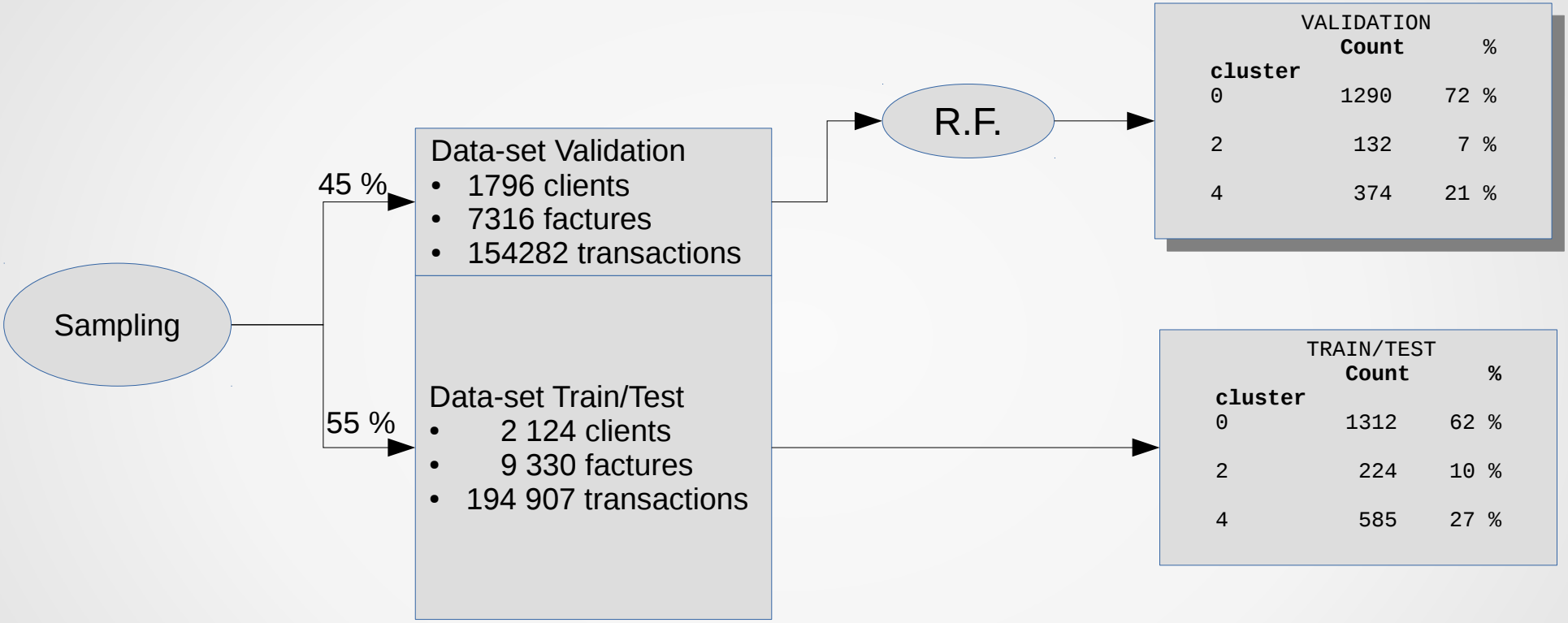
penalty=L1
C=1000.0
loss='squared_hinge'
dual=False

	Segment 0	Segment 2	Segment 4
Précision	92 %	71 %	89 %
Recall	98 %	79 %	85 %
Spécificité	97 %	97 %	95 %
F-mesure	95 %	75 %	87 %

Parcours Datascientist : projet 5

Validation

Validation : data-set prediction



VALIDATION

cluster	Count	%
0	1290	72 %
2	132	7 %
4	374	21 %

TRAIN/TEST

cluster	Count	%
0	1312	62 %
2	224	10 %
4	585	27 %

Validation : Segment 2 vs RFM = 111

CustomerID	Frequency	Recency	Monatary	neg_recency	R_score	F_score	M_score	RFM
12839	14	2	5591.42	-2	1	1	1	111
...								

get_market_segment()

RFM threshold matrix

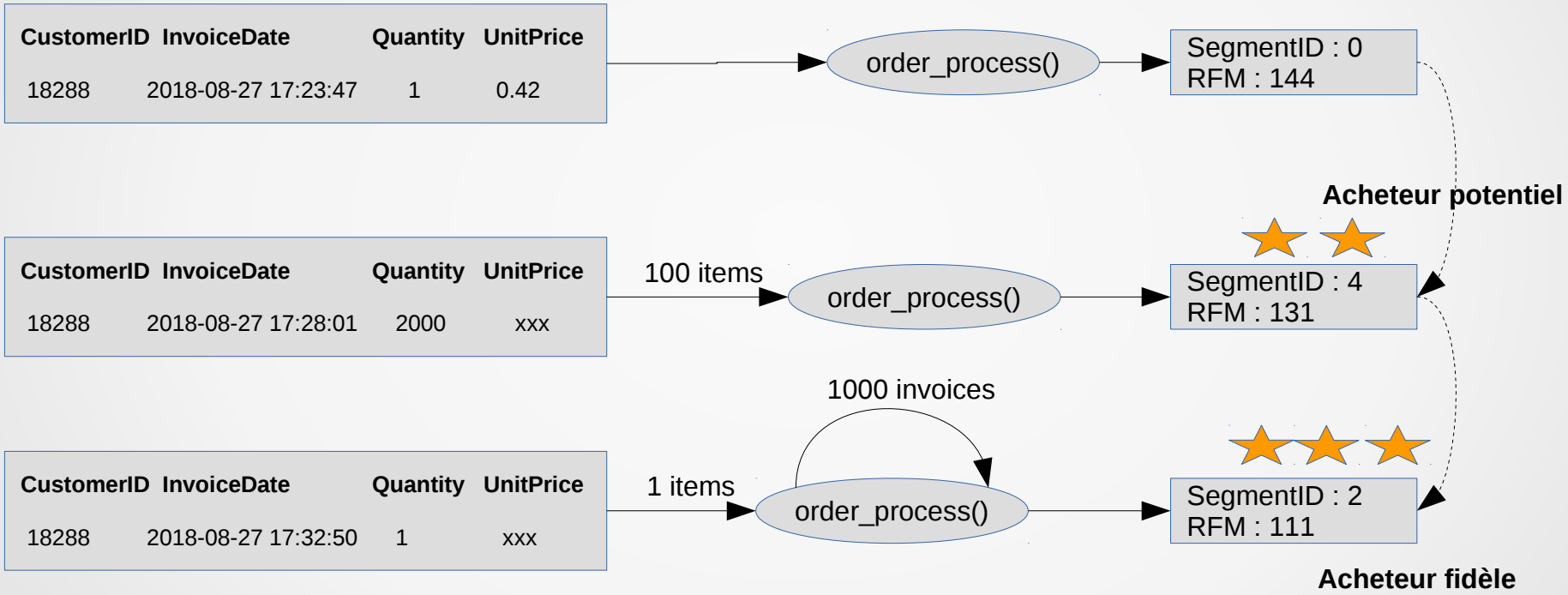
	Frequency	Recency	Monatary	neg_recency
Q1	1.0	16.0	296.170	-140.0
Q2	2.0	49.0	654.025	-49.0
Q3	5.0	140.0	1552.130	-16.0

```
0: [13013]
2: [12839, 12856, 12901, 12921, 12971, 13050, 13069, 13081]
4: [12935, 13012, 13090, 13126]
```

Segment 0 : 1
Segment 2 : 8
Segment 4 : 4

Segment 2
Précision : 8/13= 60 %

Validation : Market segment path



Conclusions

- Problème ~ linéairement séparable
- Traitement NLP : nécessite d'importantes ressources
- R.F : qualité satisfaisante de prédiction.
- Améliorations / évolutions:
  - Infos sur client → amélioration de la prédiction
  - Re-calcul de la matrice de seuils RFM
  - Intégration en environnement BIG DATA
    - Traitement d'une facture > 100 transactions
    - Traitement NLP sur nb. descriptions > 4000
    - Traitement simultané de factures

Parcours Datascientist : projet 5

Annexes

Annexe 1 : fichiers du projet

Annexe 2 : organisation et processus de l’étude

Annexe 3 : Variables issues du score RFM

Annexe 4 : variables issues du traitement NLP

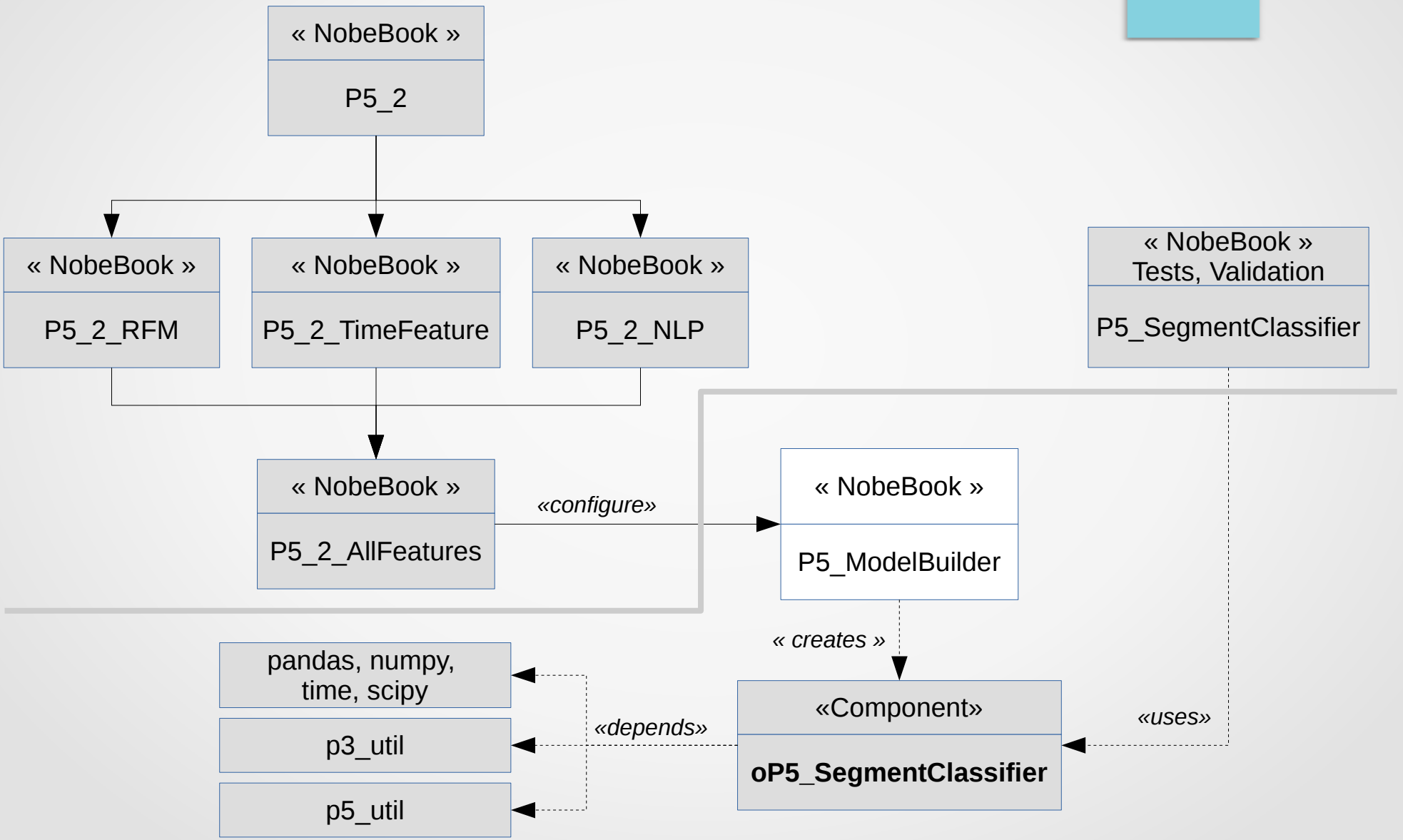
Annexe 5 : variables issues de la date de facturation

Annexe 6 : API WEB

Annexe 1 : fichiers du projet

- **Fichiers source python :**
  - p3_util_plot.py : utilitaires d'affichage issus du projet P3
  - p3_util.ppy : utilitaires du projet P3
  - p5_util_plot.py : utilitaires d'affichage issus du projet P5 (projet courant)
  - p5_util.py : utilitaires issus du projet P5 (projet courant)
  - P5_ModelBuilder.py : générateur de modèle de prédiction
  - P5_SegmentCassifier.py : implémentation du modèle de prédiction
- **Notebooks de l'alnalyse exploratoire :**
  - P5_2.ipynb : nettoyage / exploration
  - P5_2_RFM.ipynb : analyse des features dérivées du score RFM
  - P5_2_timeFeature.ipynb : analyse des features dérivées de la date de facturation
  - P5_2_NLP.ipynb : analyse des features dérivées de la description traitées en NLP
- **Notebook des approches de modélisation :**
  - P5_2_AllFeature.ipynb : algorithmes de M.L. non supervisés et supervisés.
- **Notebook de test / validation**
  - P5_SegmentClassifier.ipynb
- **Rapport sous forme de présentation pdf:**
  - Openclassrooms_ParcoursDatascientist_P5.pdf
- **Points d'entrée de l'API :**
  - Pour récupérer une liste de vols :
    - https://https://francois-bangui-oc-p4.herokuapp.com/predictor/?'*'
  - Pour récupérer l'évaluation du retard d'un vol à partir de son identifiant :
    - https://https://francois-bangui-oc-p4.herokuapp.com/predictor/?flight_id=<ID>
- Pour récupérer un el
- http://localhost:5000/?customerID=12822

Annexe 2 : artefacts et processus d'étude

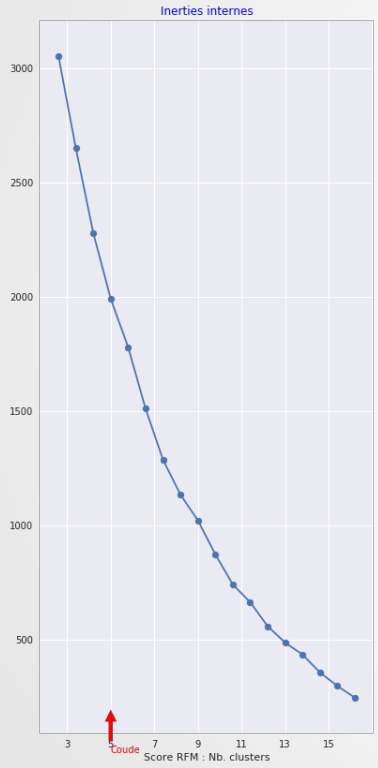


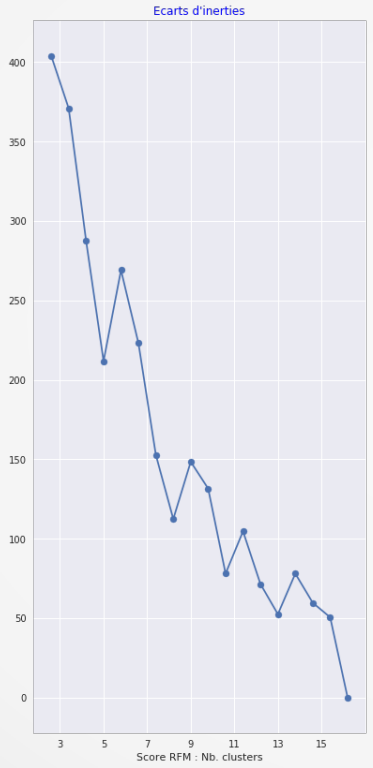
Annexe 3 : Étude RFM

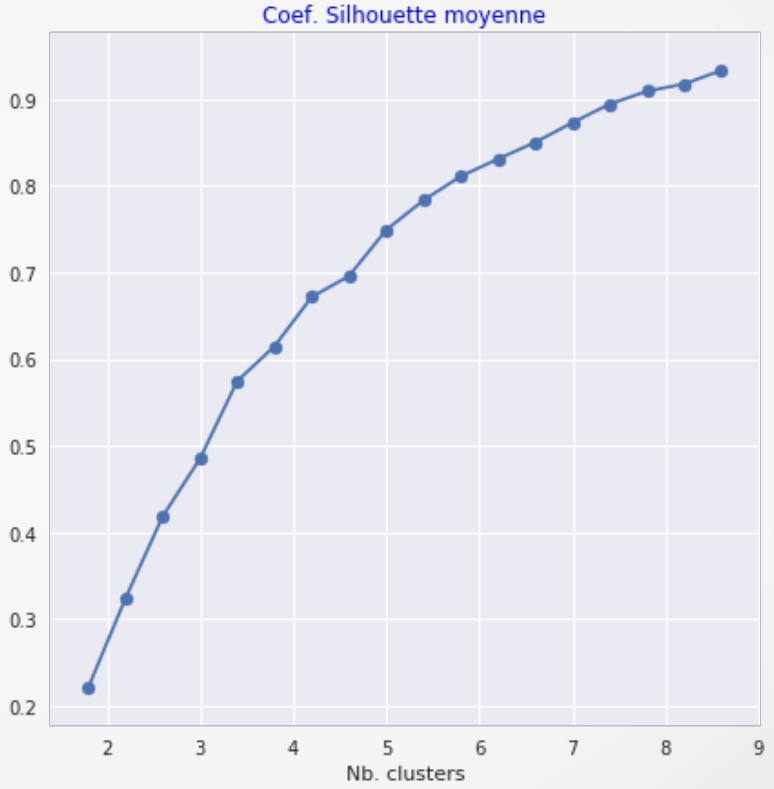
RFM : Kmeans Clustering

Encodage RFM

- 2373 clients
- 58 dimensions

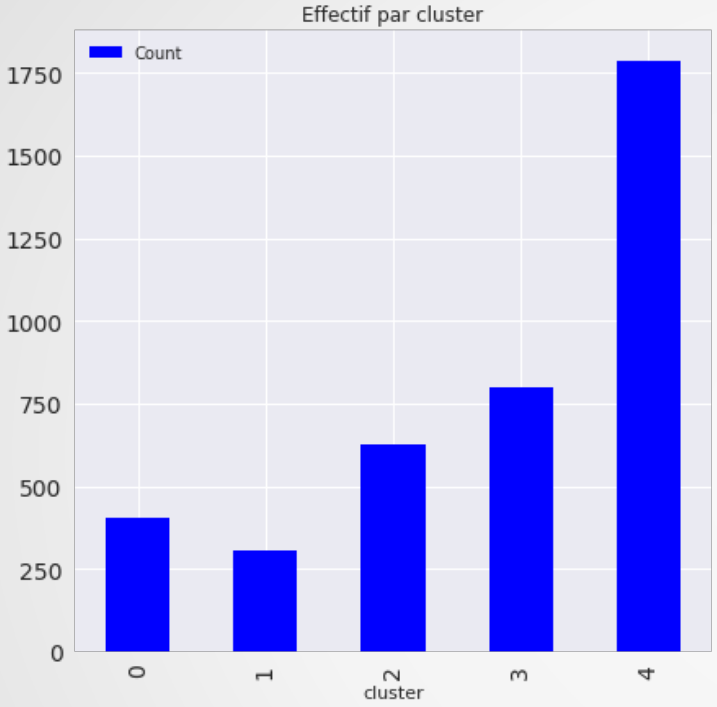






Nb optimal de clusters : 5

Clustering RFM : Kmeans effectifs par cluster

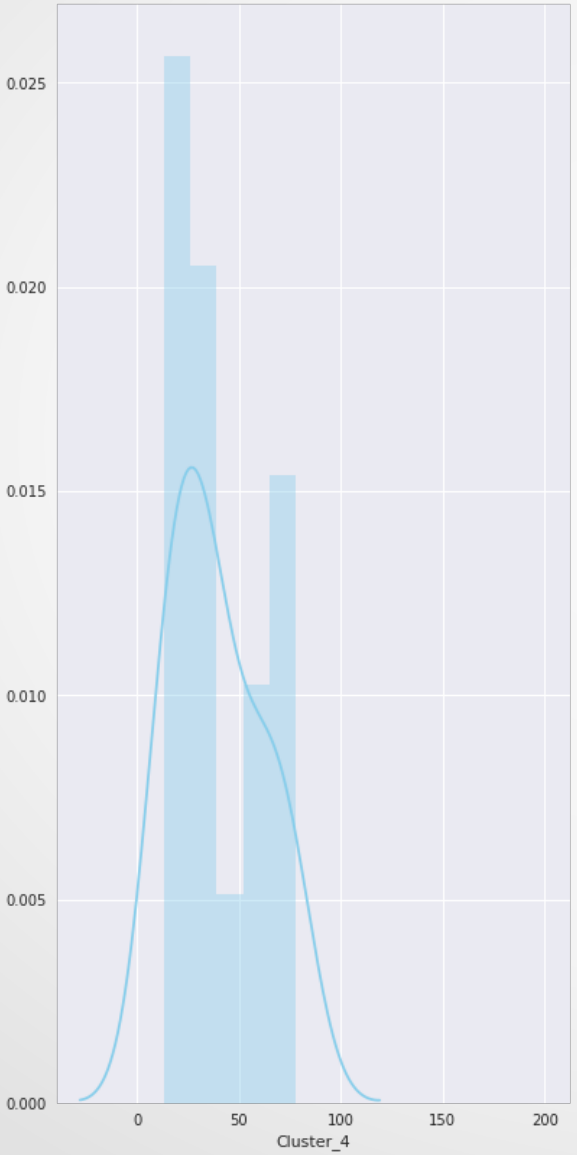


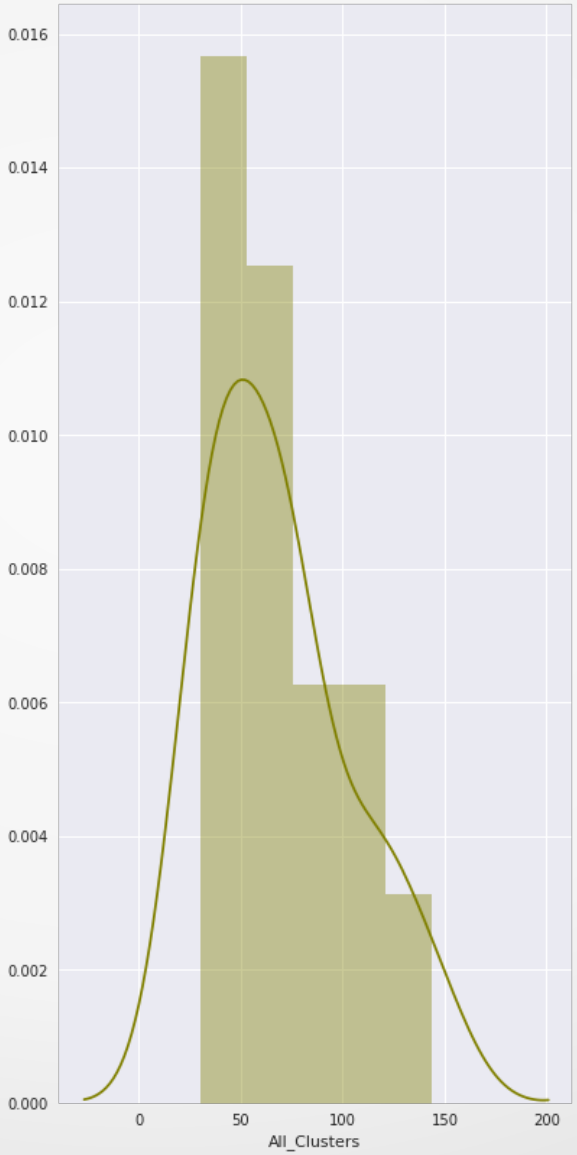
- Clusters : > 300
- Exclusion mutuelle

Clusters distincts :
- 111, 411, 422, 433, 444

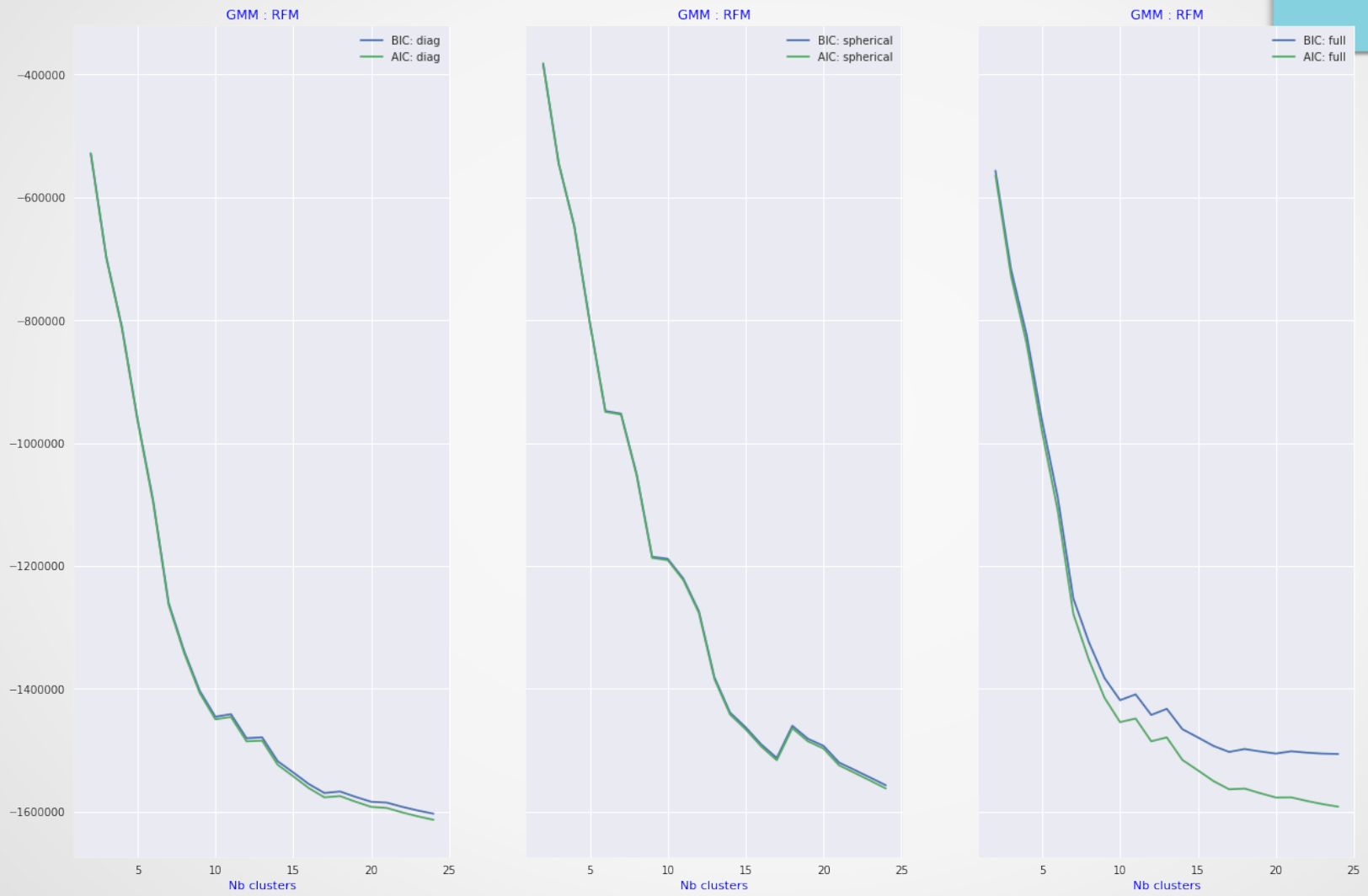
RFM	Cluster_0	Cluster_1	Cluster_2	Cluster_3	Cluster_4	All_segments
111	402	0	0	0	0	402
112	0	0	0	0	78	78
113	0	0	0	0	16	16
114	0	0	0	0	1	1
121	0	0	0	0	75	75
122	0	0	0	0	115	115
123	0	0	0	0	38	38
124	0	0	0	0	13	13
131	0	0	0	0	16	16
132	0	0	0	0	40	40
133	0	0	0	0	61	61
134	0	0	0	0	19	19
141	0	0	0	0	4	4
142	0	0	0	0	12	12
143	0	0	0	0	19	19
144	0	0	0	0	55	55
411	0	305	0	0	0	305
412	0	0	0	0	144	144
413	0	0	0	0	34	34
421	0	0	0	0	115	115
422	0	0	0	365	0	365
423	0	0	0	0	161	161
424	0	0	0	0	80	80
431	0	0	0	0	33	33
432	0	0	0	0	161	161
433	0	0	0	433	0	433
434	0	0	0	0	186	186
441	0	0	0	0	30	30
442	0	0	0	0	65	65
443	0	0	0	0	218	218
444	0	0	626	0	0	626

Clustering RFM : distributions



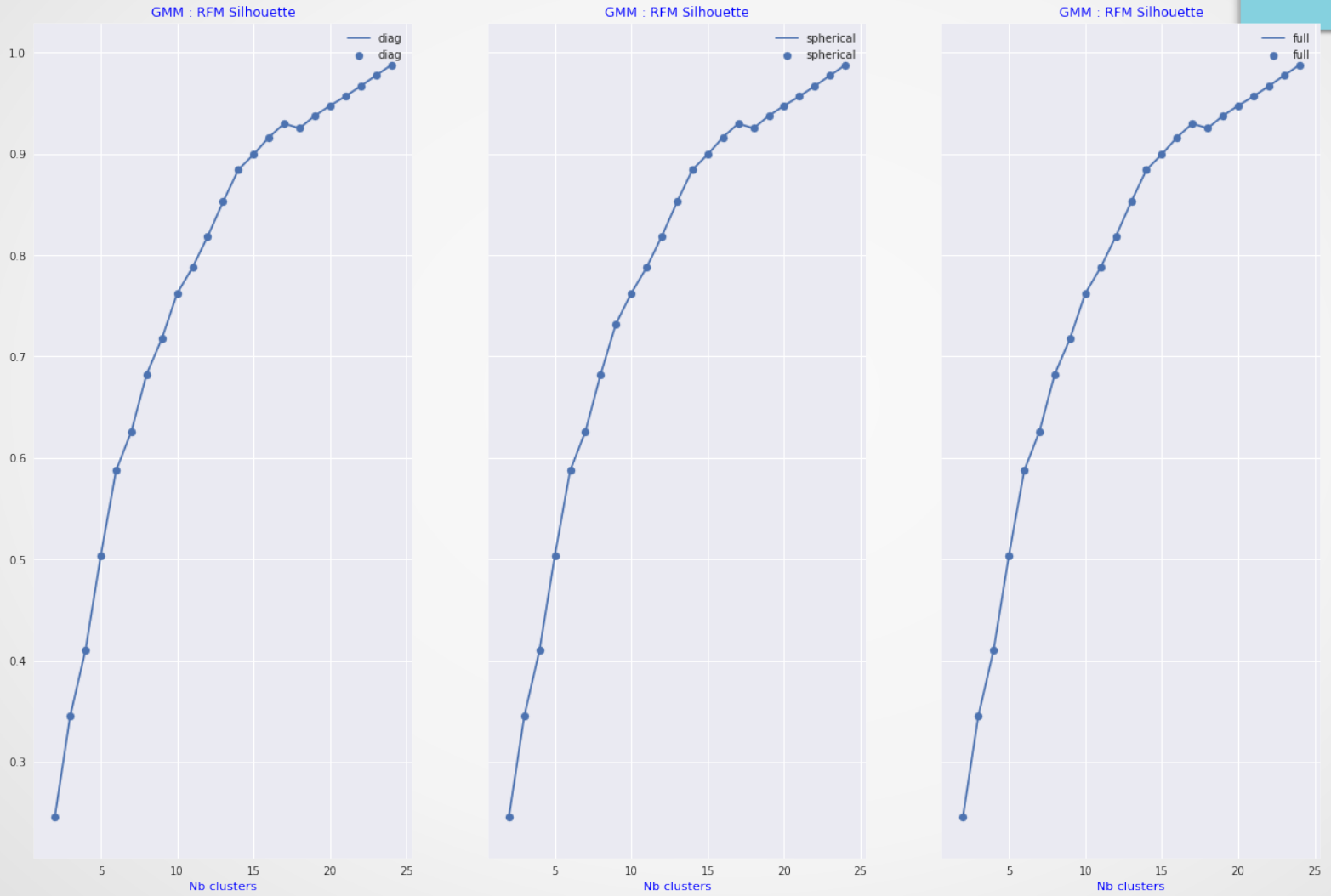


Clustering RFM : GMM models

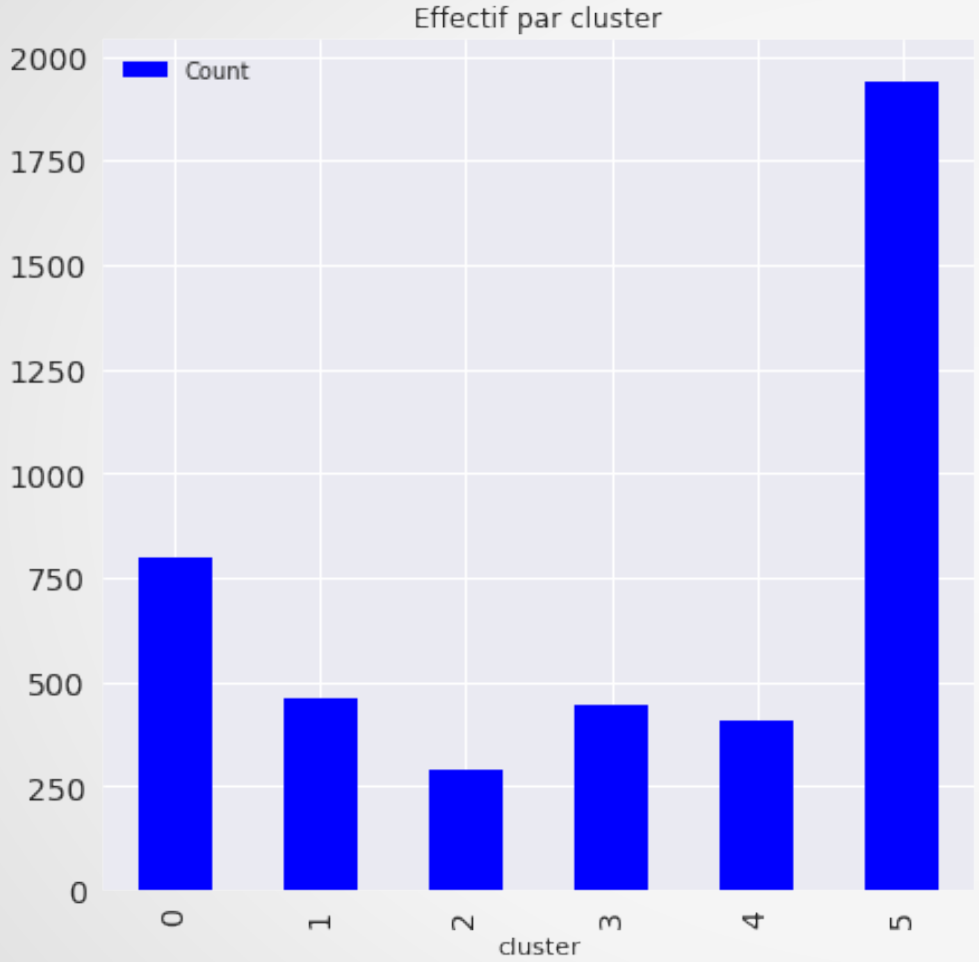


Nb clusters: 6

Clustering RFM : GMM silhouette



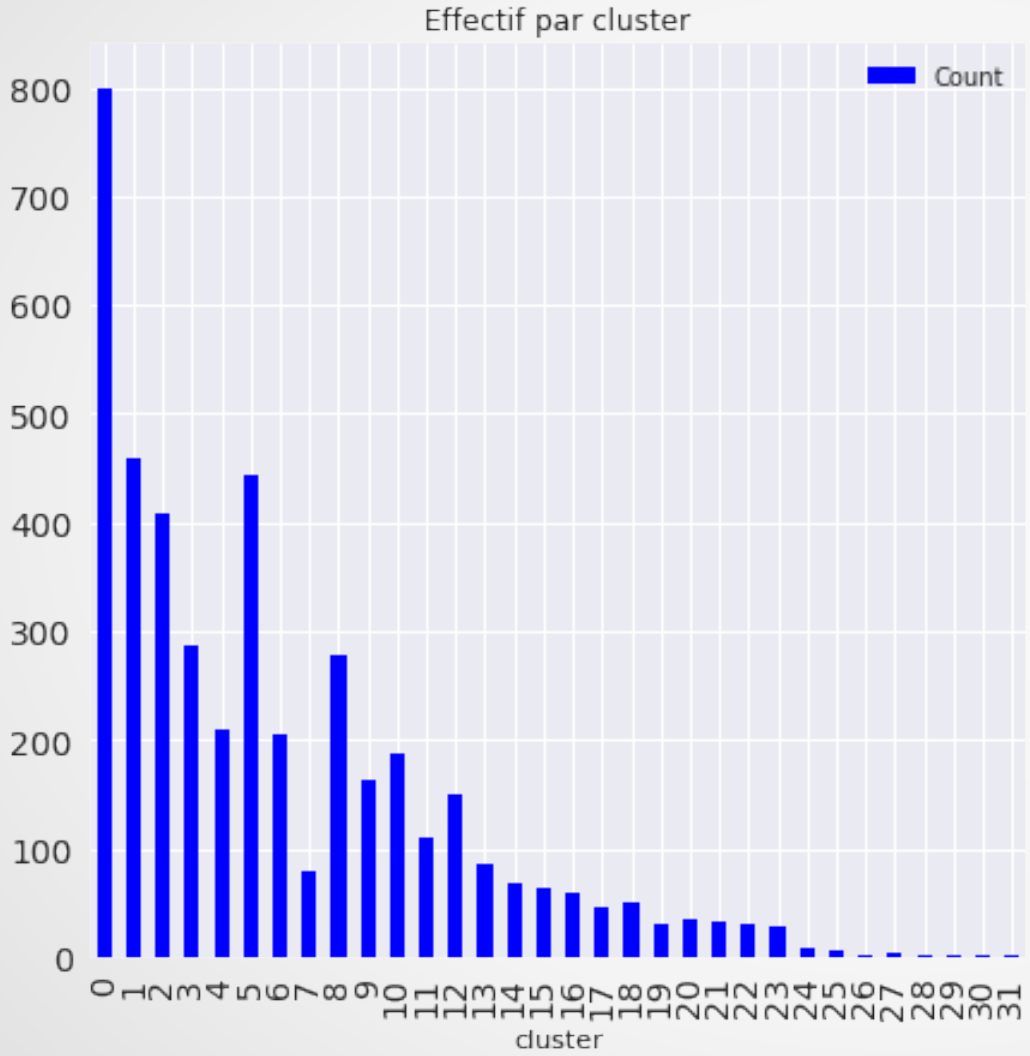
Clustering RFM : Mapping cluster/RFM (1)




```
Cluster : 0 RFM = ['444']
Cluster : 1 RFM = ['443']
Cluster : 2 RFM = ['433']
Cluster : 3 RFM = ['111']
Cluster : 4 RFM = ['422']
Cluster : 5 RFM = ['441' '421' '411'
'442' '132' '122' '144' '431' '133'
'432' '121' '423'
 '131' '434' '112' '142' '143' '412'
'123' '134' '424' '124' '413' '141'
 '113' '114' '414']
```

5 clusters distincts

Clustering RFM : Mapping cluster/RFM (2)




```
Cluster : 0 RFM = ['444']
Cluster : 1 RFM = ['443']
Cluster : 2 RFM = ['422']
Cluster : 3 RFM = ['433']
Cluster : 4 RFM = ['432']
Cluster : 5 RFM = ['111']
Cluster : 6 RFM = ['421']
Cluster : 7 RFM = ['412']
Cluster : 8 RFM = ['411']
Cluster : 9 RFM = ['122']
Cluster : 10 RFM = ['423']
Cluster : 11 RFM = ['442']
Cluster : 12 RFM = ['434']
Cluster : 13 RFM = ['121']
Cluster : 14 RFM = ['133']
Cluster : 15 RFM = ['112']
Cluster : 16 RFM = ['144']
Cluster : 17 RFM = ['132']
Cluster : 18 RFM = ['123']
Cluster : 19 RFM = ['441']
Cluster : 20 RFM = ['431']
Cluster : 21 RFM = ['134']
Cluster : 22 RFM = ['424']
Cluster : 23 RFM = ['143']
Cluster : 24 RFM = ['124']
Cluster : 25 RFM = ['131']
Cluster : 26 RFM = ['413']
Cluster : 27 RFM = ['142']
Cluster : 28 RFM = ['113']
Cluster : 29 RFM = ['141']
Cluster : 30 RFM = ['114']
Cluster : 31 RFM = ['414']
```

Covariance sphérique
32 clusters : RFM séparés

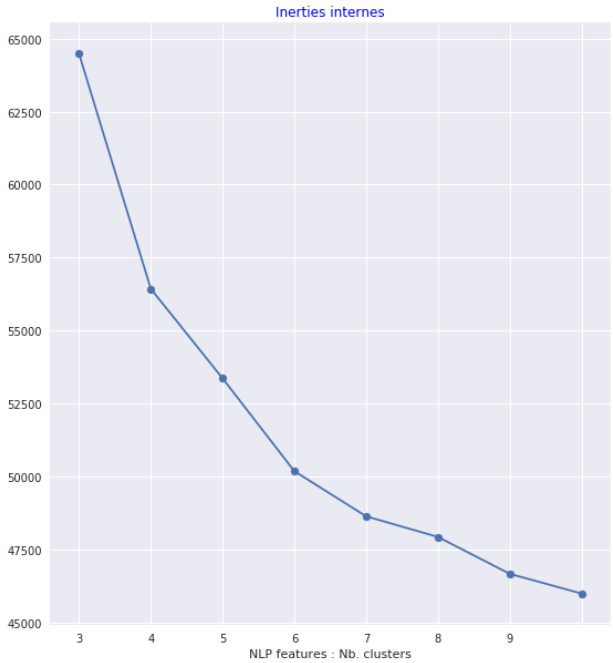
Annexe 3 : Étude NLP

NLP: Kmeans clusters

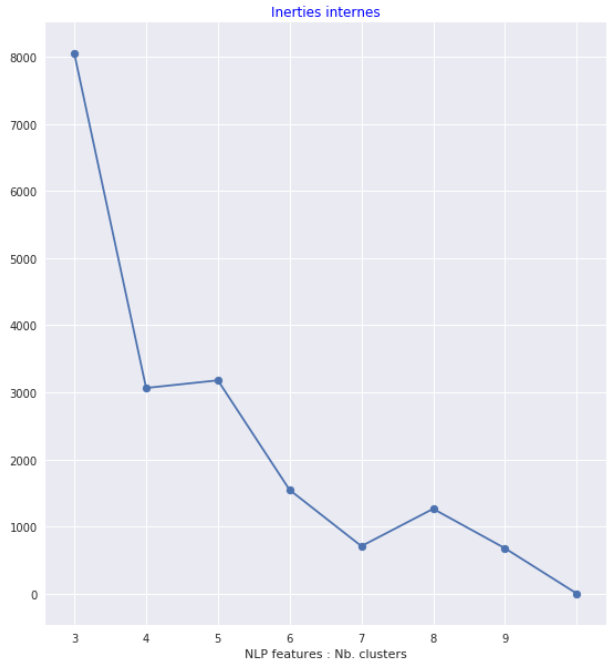
NLP

- 2373 clients
- 250 dimensions

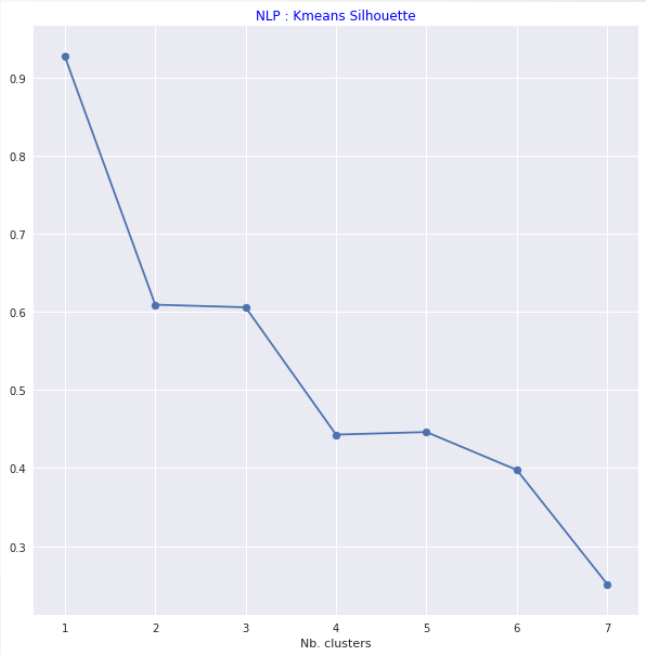
Inerties interne



Inerties interne : taux décroissance

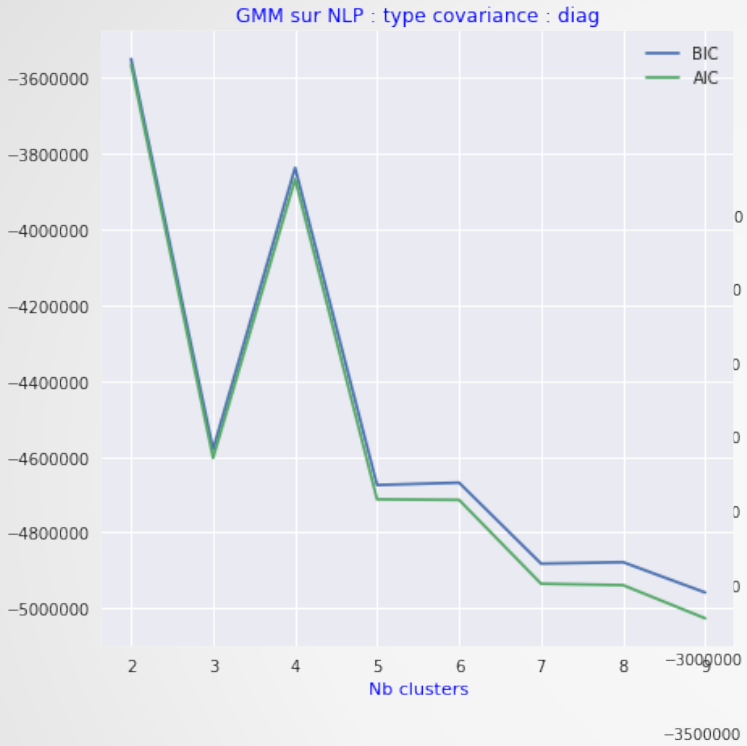


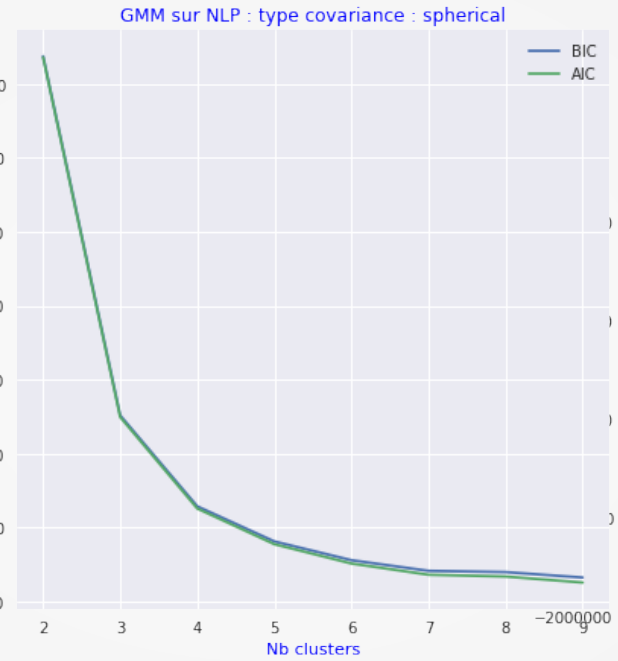
Coefficient de silhouette

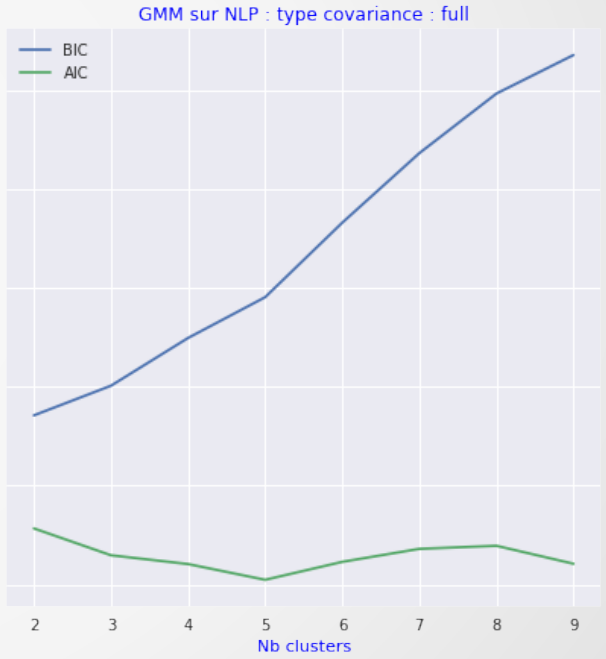


Nb optimal de clusters : 3

NLP: GMM clusters et type de covariance

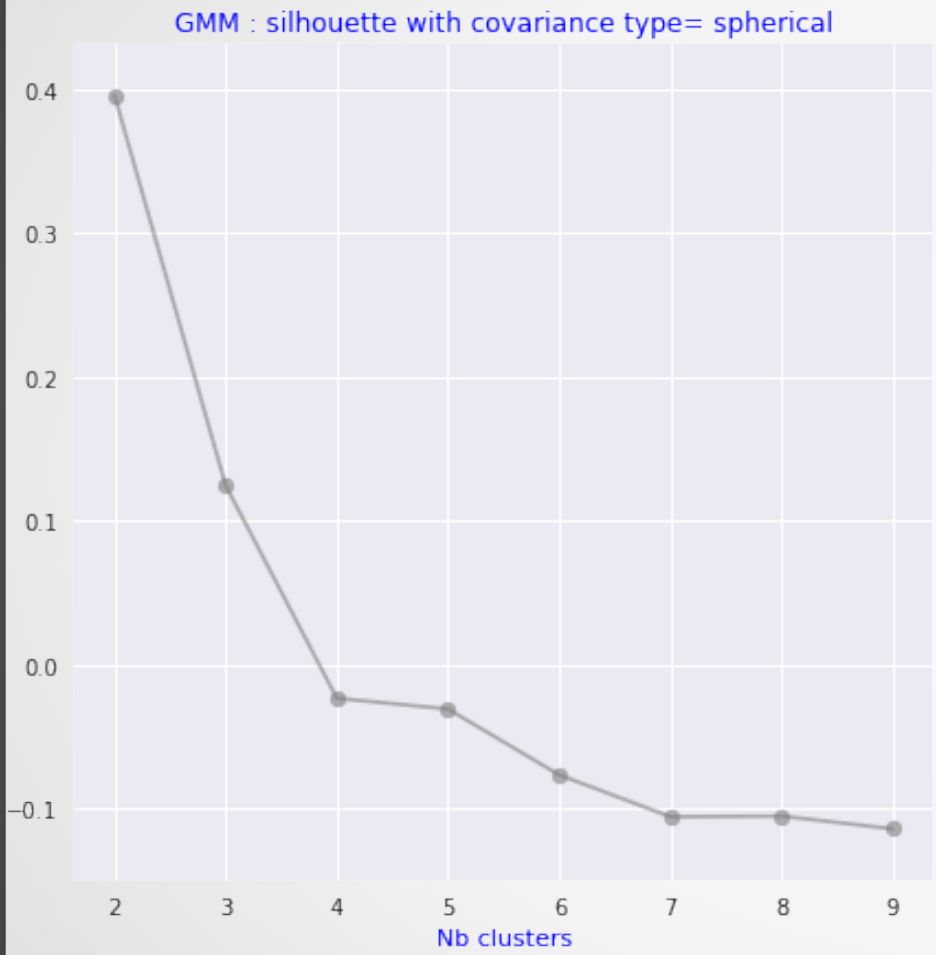


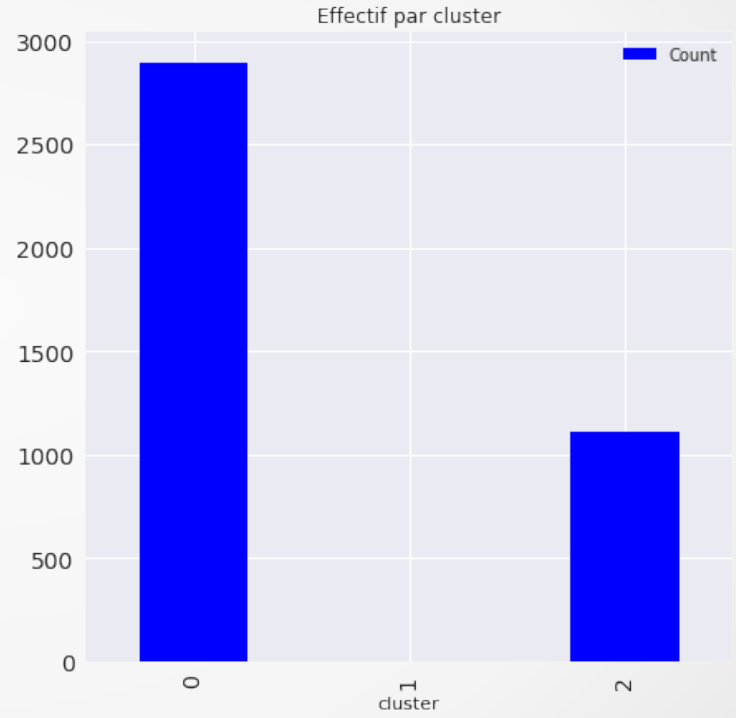




Nb optimal de clusters : 3
Co-variance des axes : sphérique

NLP: GMM clusters et silhouette

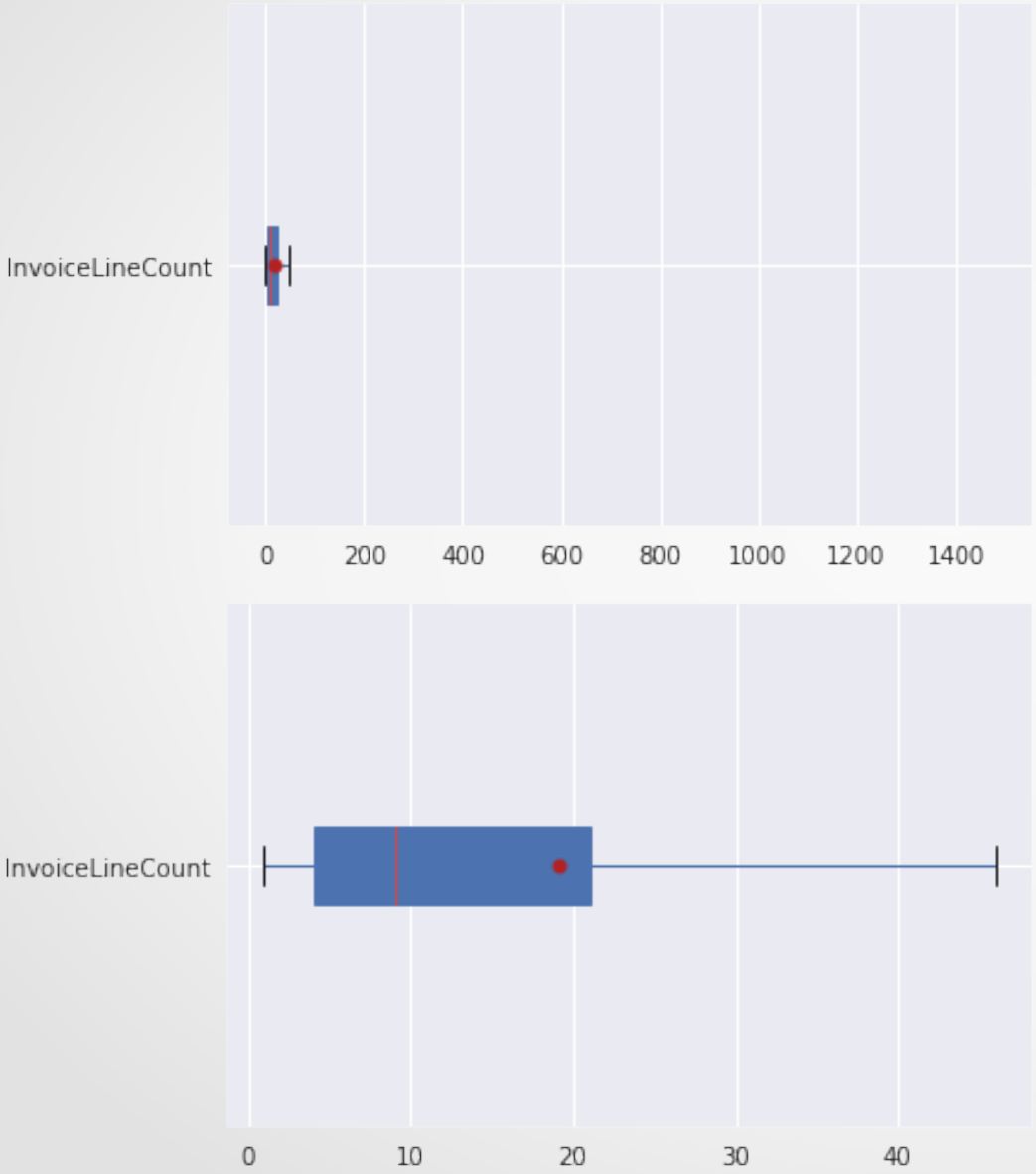




Nb optimal de clusters : 3
Convergence : True

cluster	Count
0	2896
1	1
2	1113

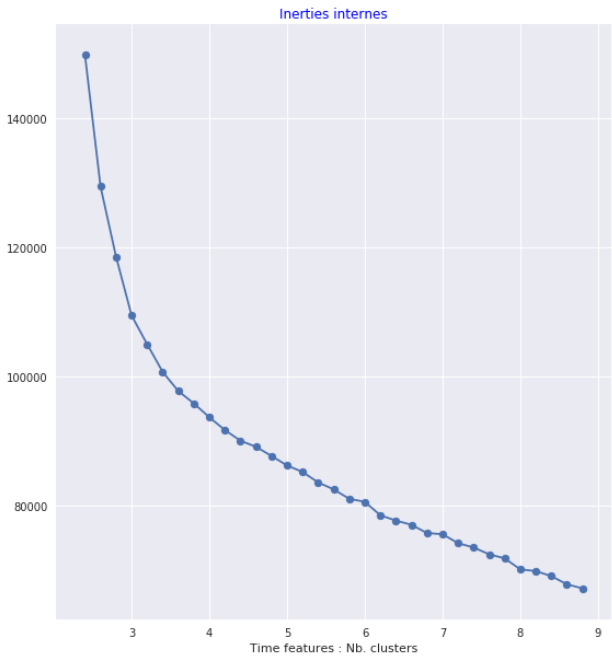
NLP: Cluster 1

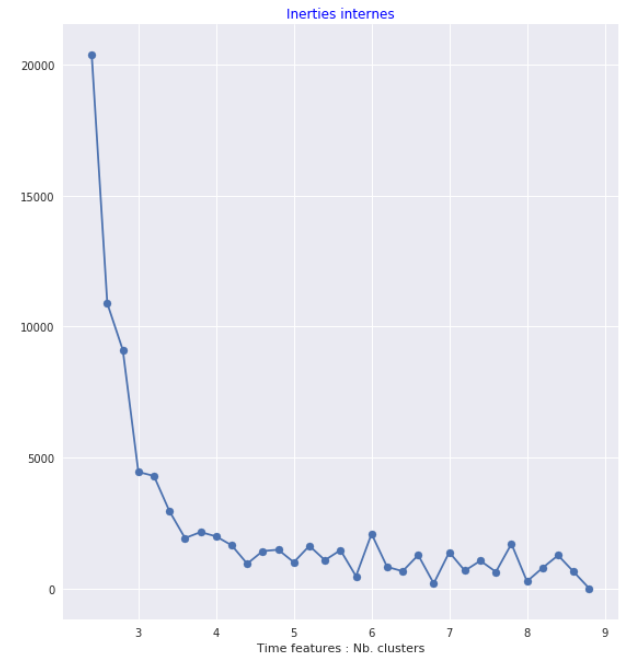



```
Cluster : 1
Customer ID : 17841
Transactions : 1484
```

Annexe 4 : Étude time

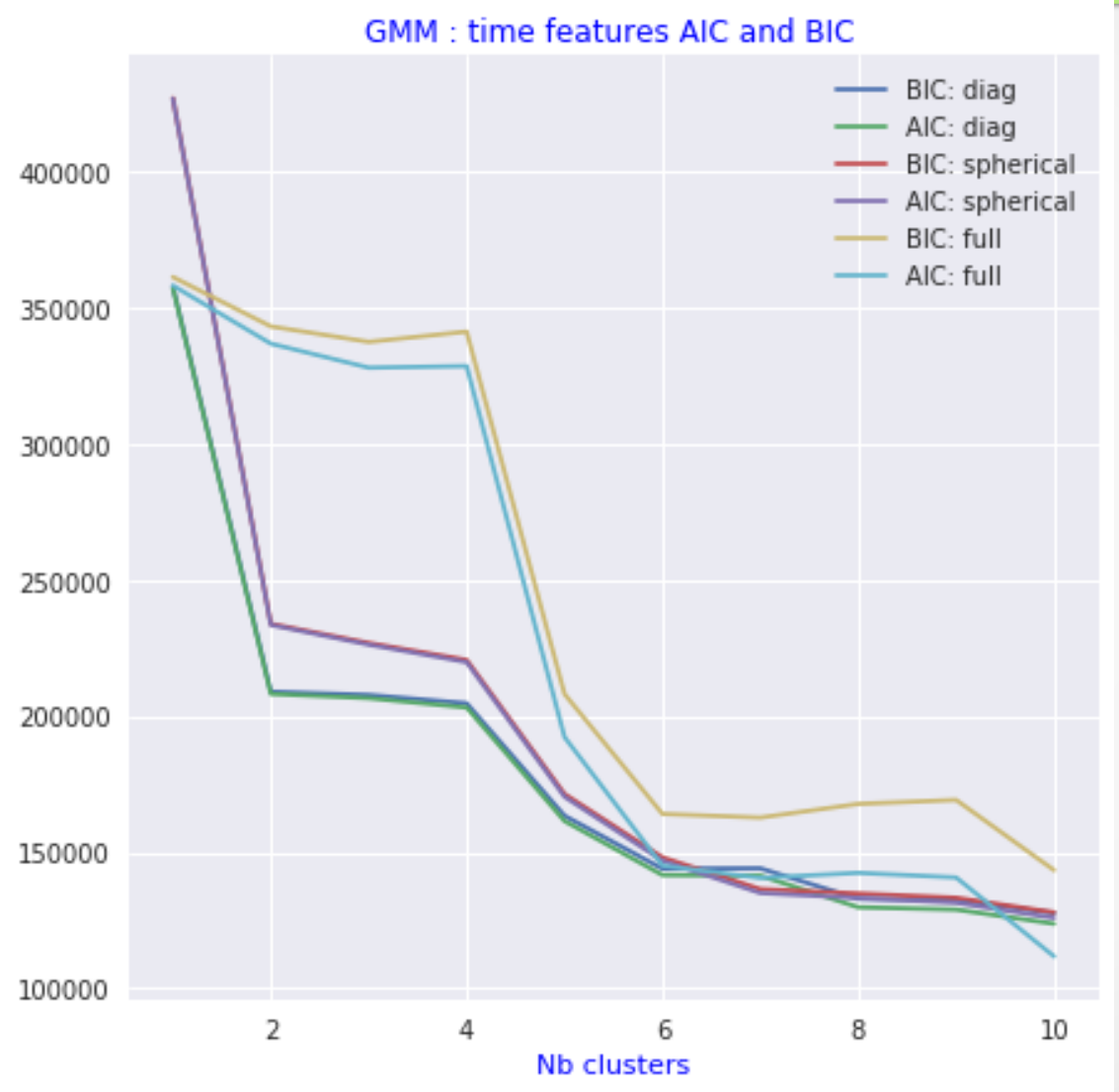
Time : Kmeans clustering





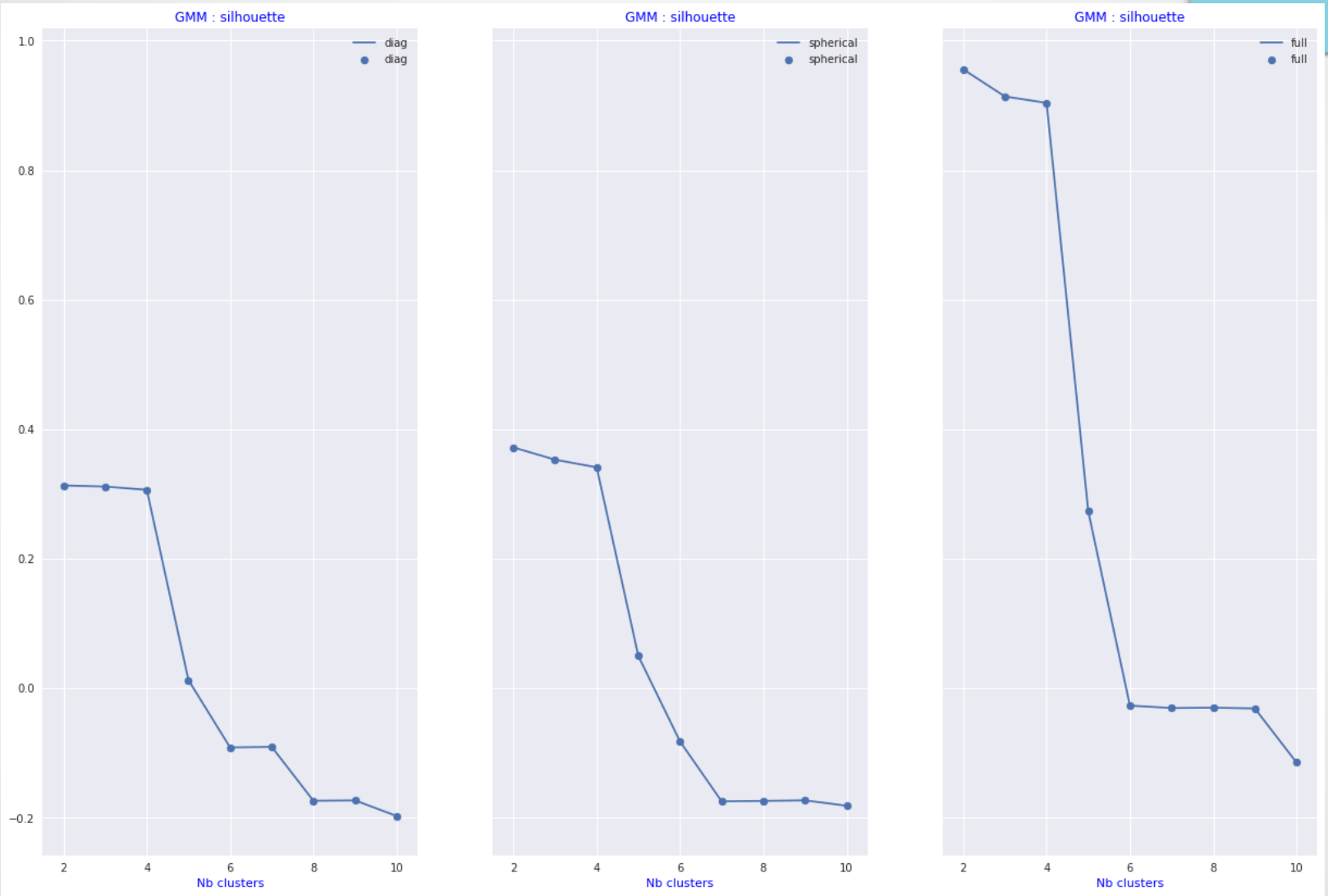
Nb optimal de clusters : 3

Time : GMM clustering vs AIC and BIC



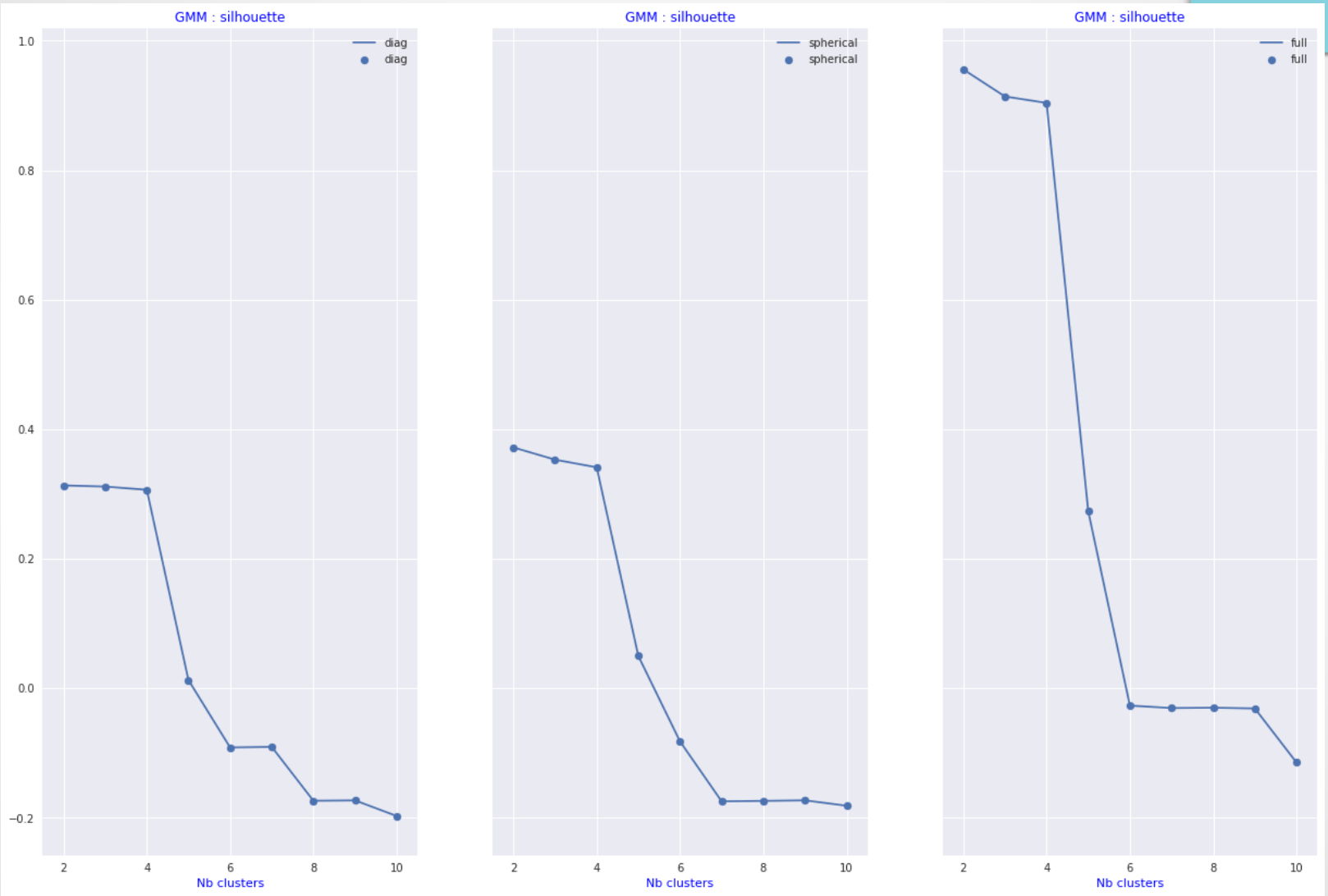
Nb optimal de clusters : 6

Time : GMM clustering vs Silhouette



Nb optimal de clusters : 4
Type covariance : Full

Time : GMM clustering vs Silhouette



Nb optimal de clusters : 4
Type covariance : Full

Annexe 6 : API WEB

- Informations du data-set :
  - http://localhost:5000/?*

    { "_results":[{ "customer_count": "3921, "invoice_count": "16661, "invl_count": "349216}] }

- Informations client
  - http://localhost:5000/?customerID=12822

    { "_results":
    [{ "**customerID**":12822 ,"**marketID**":2 ,"**invoice_count**":16
    ,"**item_count**":13756 ,"**invl_count**":72 ,"**mean_unit_price**":2.28
    ,"**incomes**":31308.58 ,"**old_date**":2011-09-13 13:46:00
    ,"**new_date**":2018-08-29 12:14:08 ,"**RFM**":144 }] }

- Achat en ligne et prédiction d'un client inexistant
  - http://localhost:5000/?order&customerID=0&stockCode=22812&quantity=3&orderDate=NONE

    { "_results":[{ "customerID": "18288, "marketID": "0}] }

- Achat en ligne et prédiction d'un client existant (dataset validation)
  - http://localhost:5000/?order&customerID=0&stockCode=22812&quantity=1&orderDate=NONE