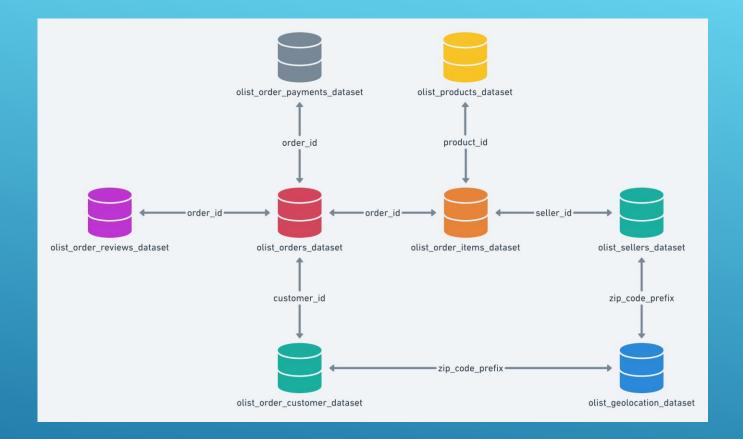
ETUDE CLIENTS OLIST

Objectifs:

- Comprendre les différents types de clients
- > Fournir une description actionnable pour l'équipe marketing
- Proposition de contrat de maintenance

ANALYSE DES DONNÉES FOURNIES



- Jonction des tables entre elles
- Nettoyage des données
- Feature engeneering

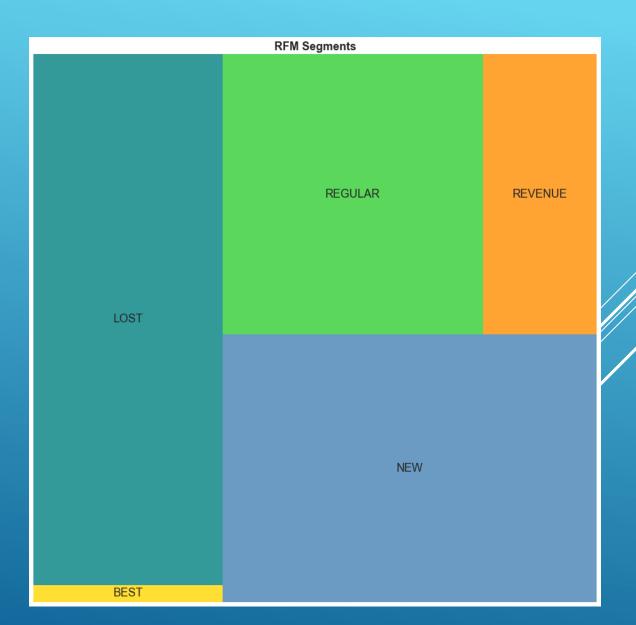
 Reste 32 variables portant sur 94925 transactions

SEGMENTATION SUPERVISÉE

Création de 3 variables:

- Recency: nombre de jours depuis la date de la dernière transaction
- Frequence: nombre de fois où le client à commandé
- Monetary: somme totale dépensée sur la période étudiée
- Attribution de notes
- Regroupement en types de comportements semblable

	RecencyMean	FrequencyMean	MonetaryMean	Group Size
segments				
Lost	153.621776	1.000000	164.583805	12445
New	30.482447	1.000000	161.069825	12505
Regular	97.187439	1.103830	103.144387	9283
Revenues	94.825771	1.000000	349.283537	3989
Valuables	30.959900	2.157895	333.162531	399

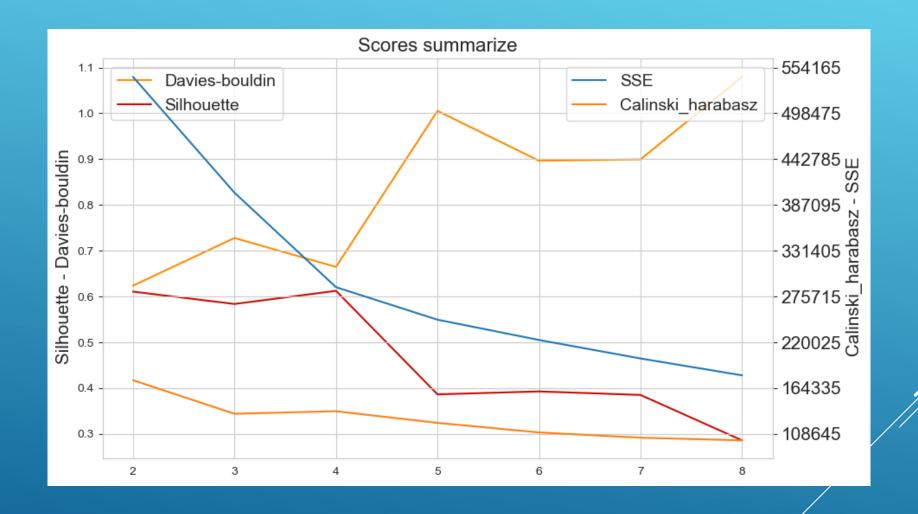


SEGMENTATION NON SUPERVISÉE

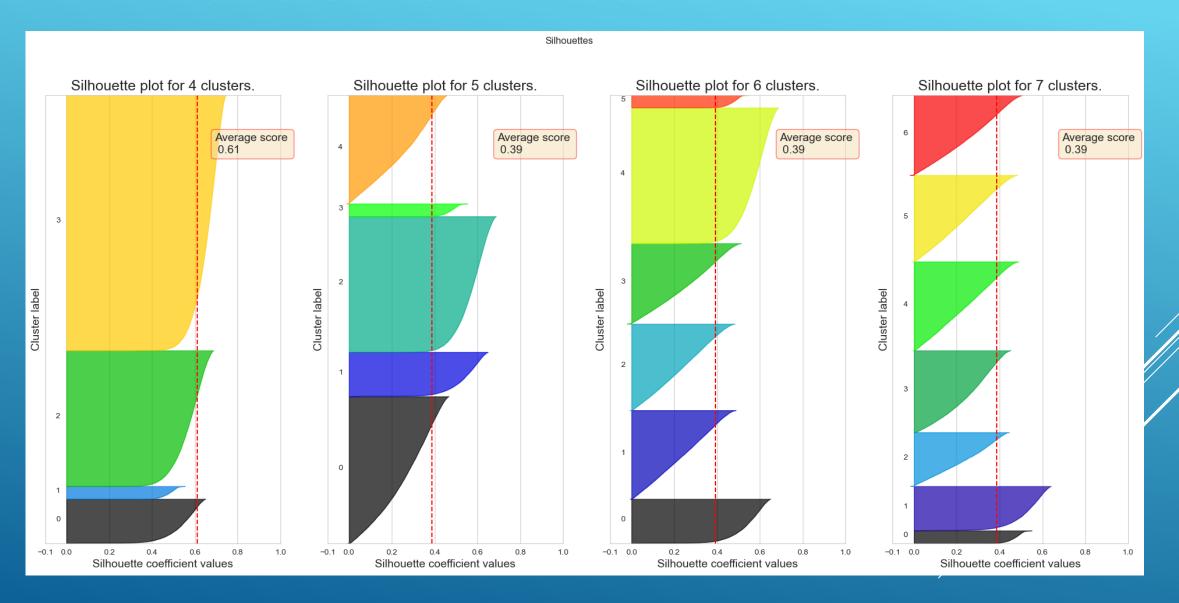
Process

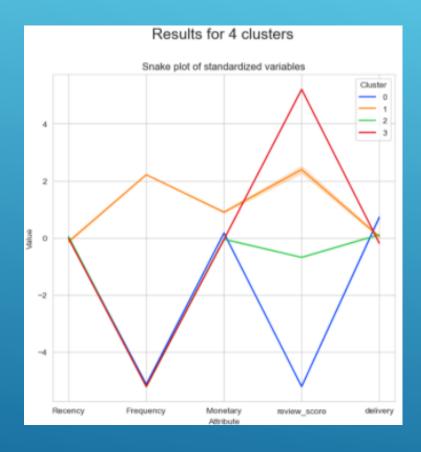
- Agrégation des données
 - Recency
 - Frequency
 - Monetary
 - Review_score
 - Delivery
- Etudes de la qualité et de l'interprétabilité du clustering
- > Sur le partitionnement retenu
 - > Etude du client type pour chaque segment
 - > Actions marketing envisageables

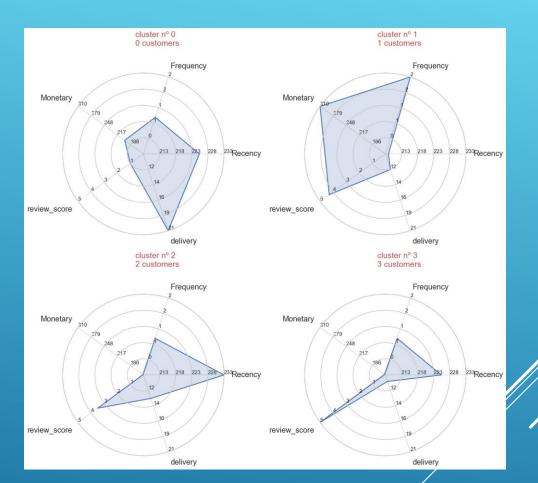
DÉTERMINATION DU NOMBRE OPTIMAL DE CLUSTERS

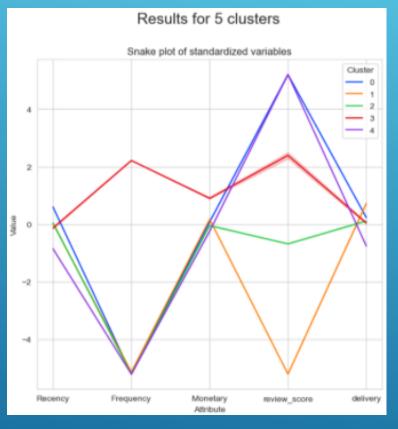


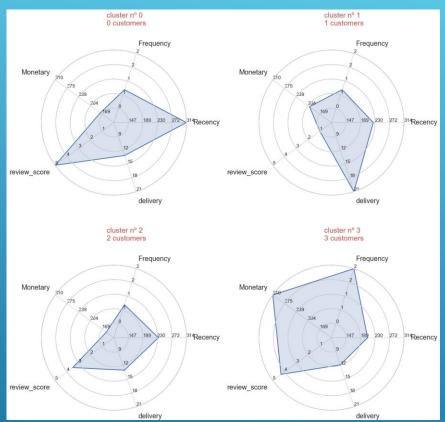
DÉTERMINATION DU NOMBRE OPTIMAL DE CLUSTERS

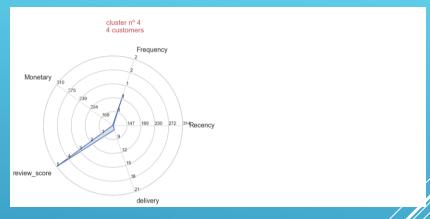


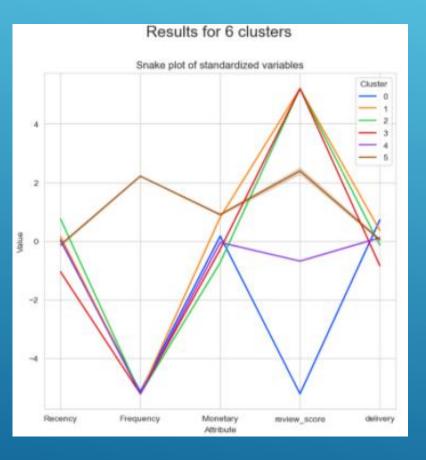


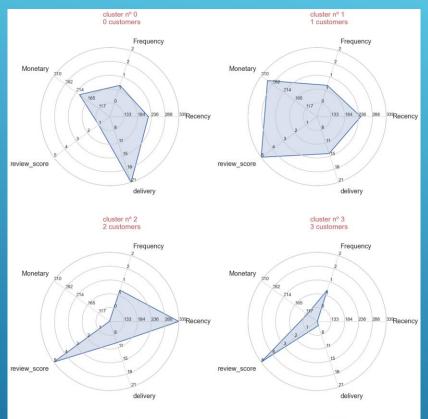


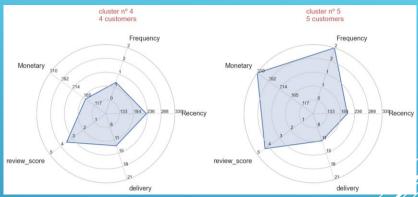


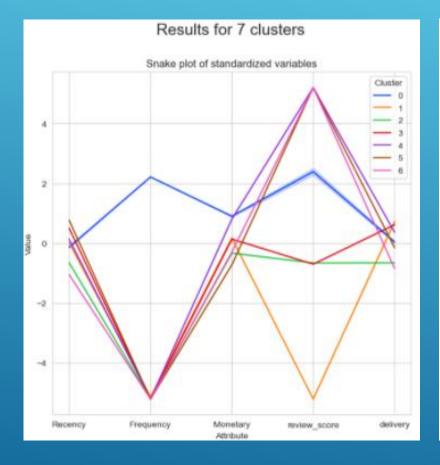


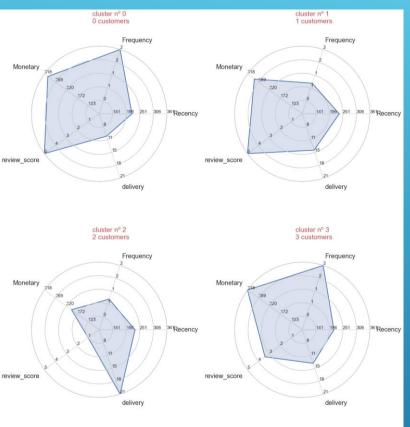


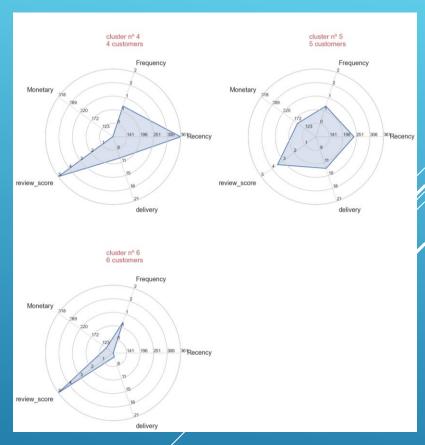




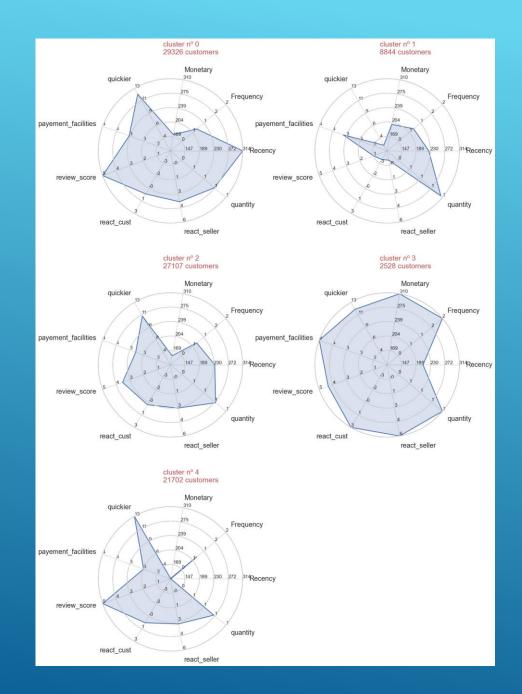






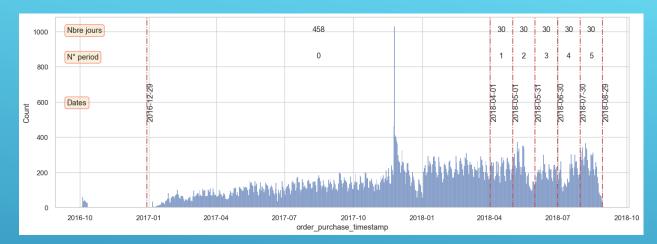


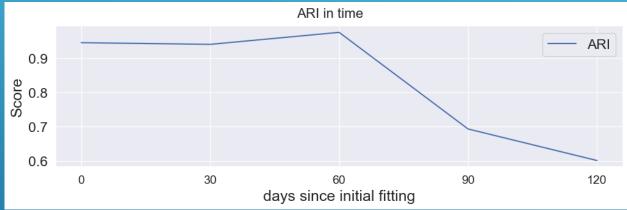
- Monetary: panie moyen
- Frequency: nombres de commandes
- Recency : nombre de jours écoulés depuis la dernière commande
- Quantity: nombre articles par commande
- react_seller: jours écoulés entre post de la reiew customer et post de la review seller
- react_cust: jours écoulés entre la réception de la commande et le post de la review
- review_score: note de satisfaction
- payement facilities: nombre de payements échelonnés
- quickier: nombre de jours d'avance de la livraison par rapport à la date estimée

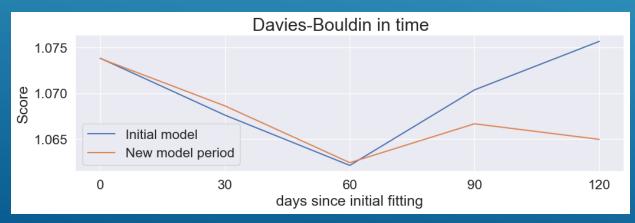


Actions marketing pour 5 clusters

- * Cluster 0: Clients perdus, on peut tenter de les relancer
- * Cluster 1: Clients ayant eu un problème avec la livraison à contacter pour enquête UX, proposer un service de livraison express/premium
- * Cluster 2: Plutôt déçus par la qualité, action marketing de type remboursement ou offre satisfait ou remboursé
- * Cluster 3: Ce sont les clients les plus importants, mais ils sont en perte de vitesse, il faut les relancer en leur offrant des bons d'achats
- * Cluster 4: Nouveaux clients à fidéliser







Stabilité du modèle

Les courbes s'infléchissent à partir de 60 jours et les scores se dégradent après 90 jours.

Je suggère une maintenance tous les deux mois afin de pouvoir suivre au mieux l'évolution de la clientèle suite au actions marketing envisagées

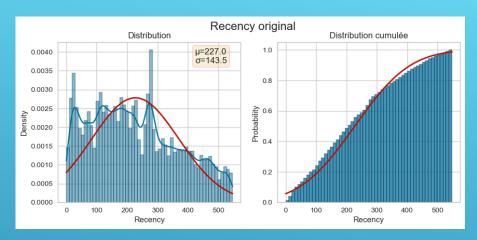
Conclusion

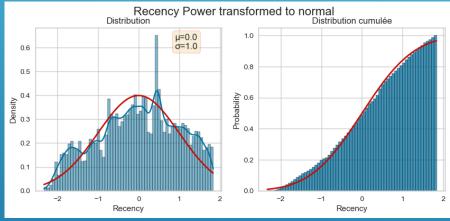
On a montré que la clientèle de Olist pouvait être partitionnée de manière non supervisée.

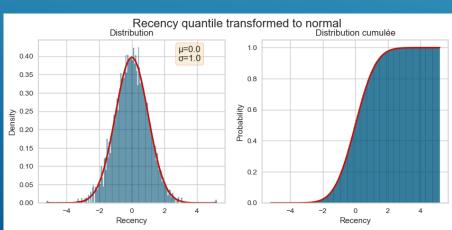
Que les profils des clients types permettent d'envisager des actions distinctes afin de mener une campagne marketing



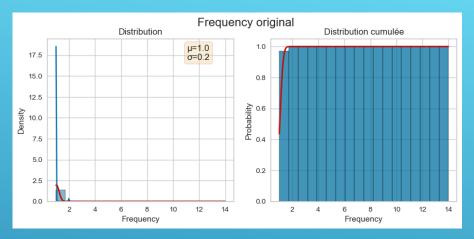
Annexes

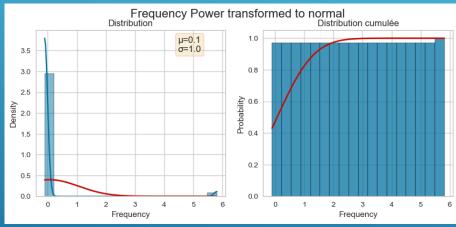


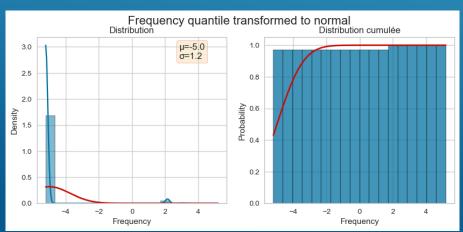




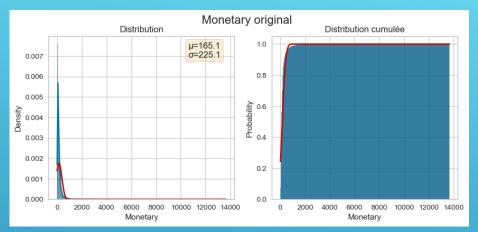
DISTRIBUTION DE RECENCY

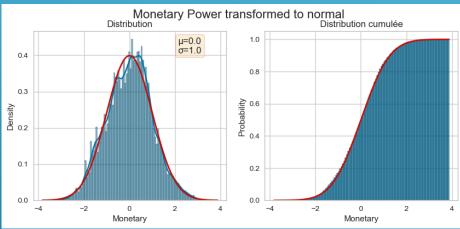


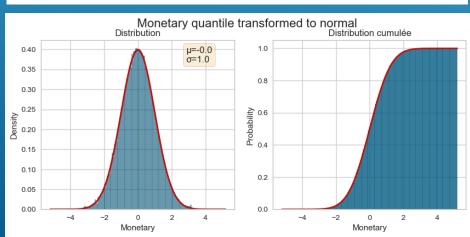




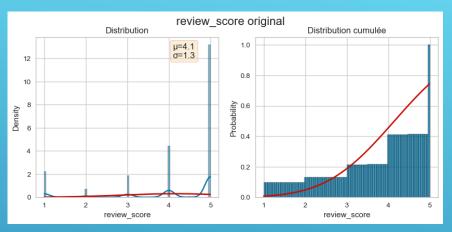
DISTRIBUTION DE FREQUENCY

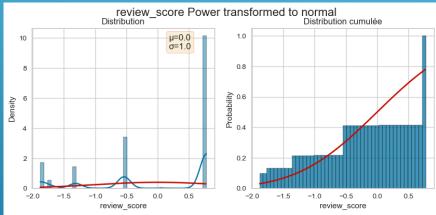


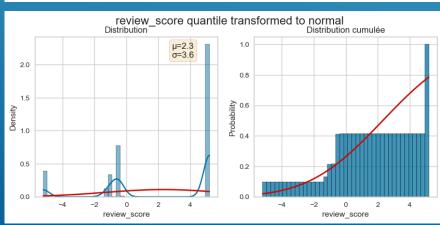




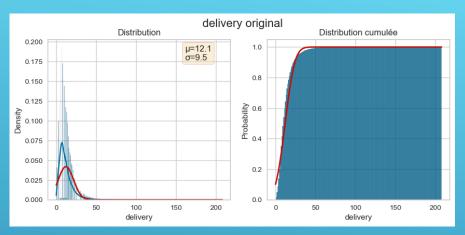
DISTRIBUTION DE MONETARY

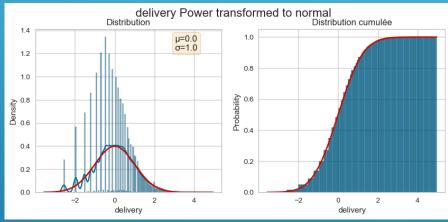


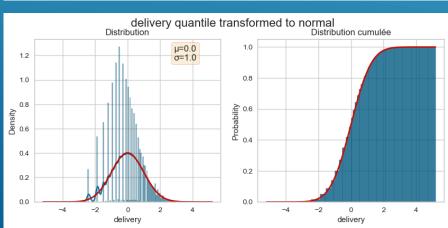




DISTRIBUTION DE REVIEW_SCORE





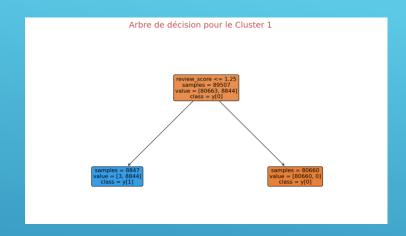


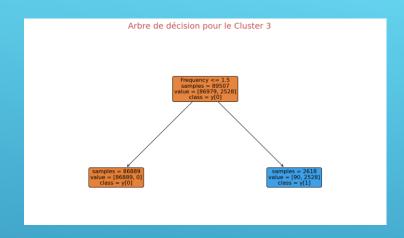
DISTRIBUTION DE DELIVERY

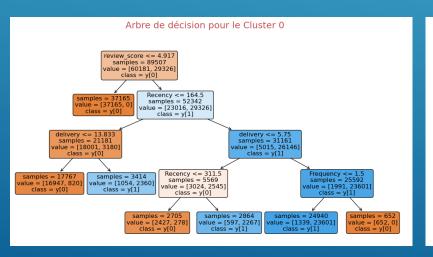
Règles de décision pour la constitution de 5 clusters

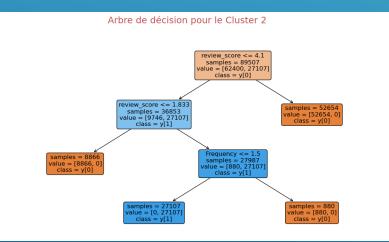
instance_count		rule_list
class_name		
		[0.6590553644041288] (review_score > 4.099999904632568) and (Recency <= 158.5) and (delivery > 13.166666507720947)
0	29326	$[0.7887981029923451] \ (review_score > 4.099999904632568) \ and \ (Recency > 158.5) \ and \ (delivery <= 5.75) \ and \ (Recency > 311.5)$
		[0.9397736617457023] (review_score > 4.099999904632568) and (Recency > 158.5) and (delivery > 5.75) and (Frequency <= 1.5)
1	8844	[0.9996609020006781] (review_score <= 4.099999904632568) and (review_score <= 1.25)
2	27107	[1.0] (review_score <= 4.099999904632568) and (review_score > 1.25) and (Frequency <= 1.5)
		[1.0] (review_score <= 4.099999904632568) and (review_score > 1.25) and (Frequency > 1.5)
3	2528	[1.0] (review_score > 4.099999904632568) and (Recency <= 158.5) and (delivery <= 13.168686507720947) and (Frequency > 1.5)
		[1.0] (review_score > 4.099999904632568) and (Recency > 158.5) and (delivery > 5.75) and (Frequency > 1.5)
		[0.9597351467430207] (review_score > 4.099999904632568) and (Recency <= 158.5) and (delivery <= 13.168686507720947) and (Frequency <= 1.5)
4	21702	[0.8758998971546109] (review_score > 4.099999904632568) and (Recency > 158.5) and (delivery <= 5.75) and (Recency <= 311.5)

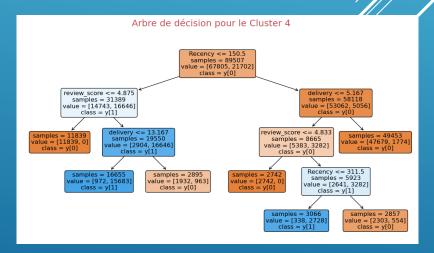
Arbres de décision pour la constitution de 5 clusters



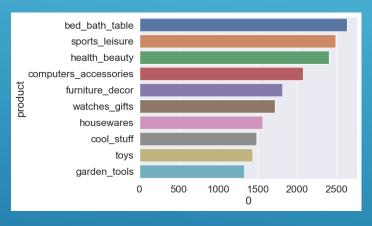


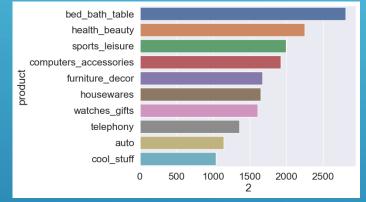


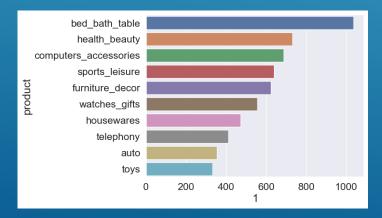


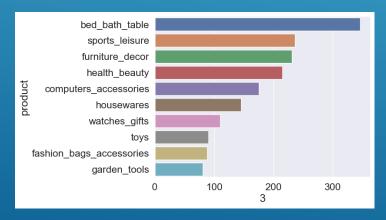


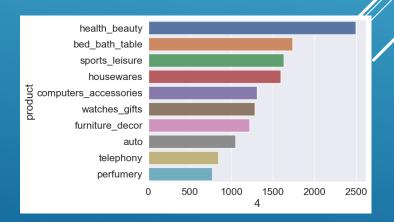
Catégories à mettre en avant pour les actions commerciales en fonction du segment visé

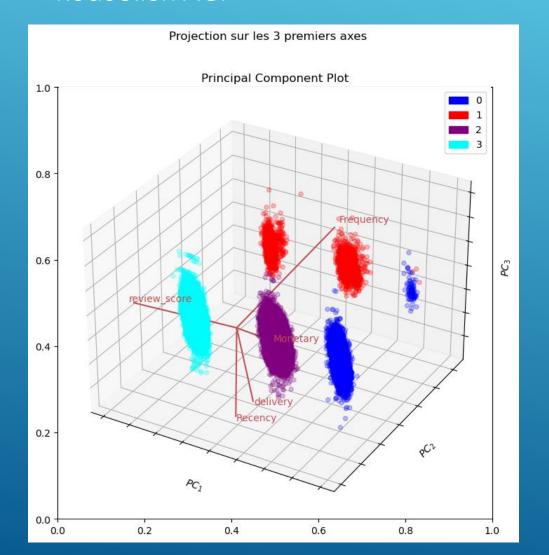




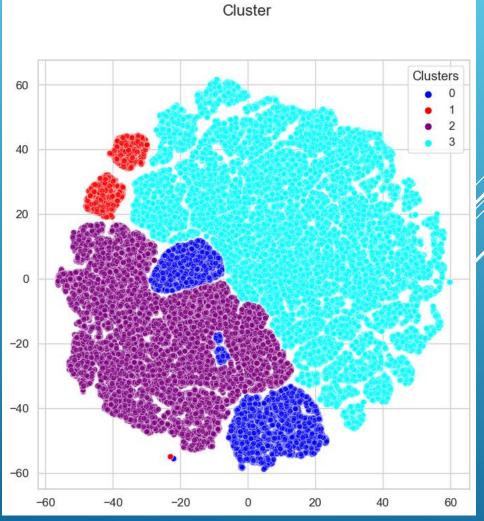


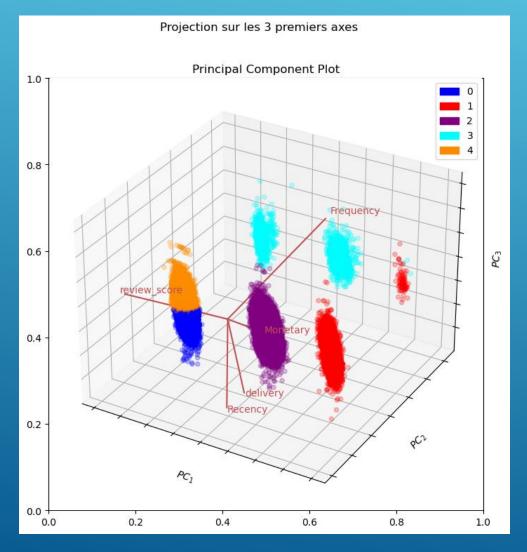




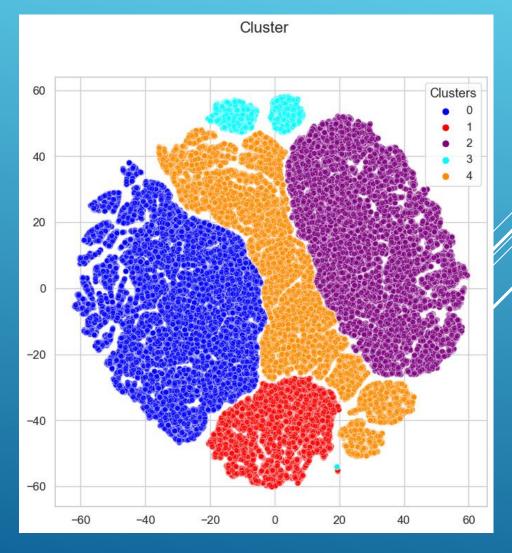


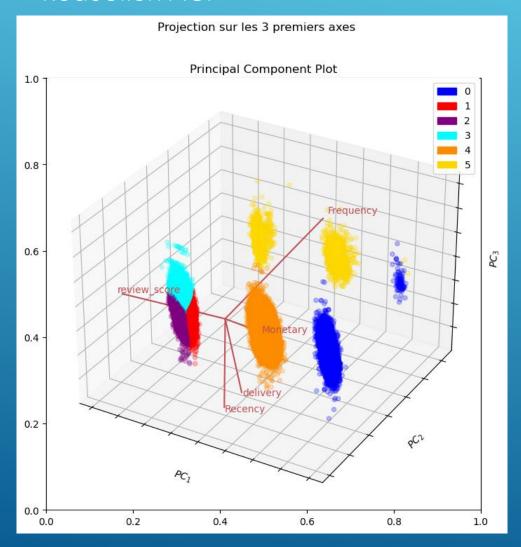
Visualisations 4 clusters



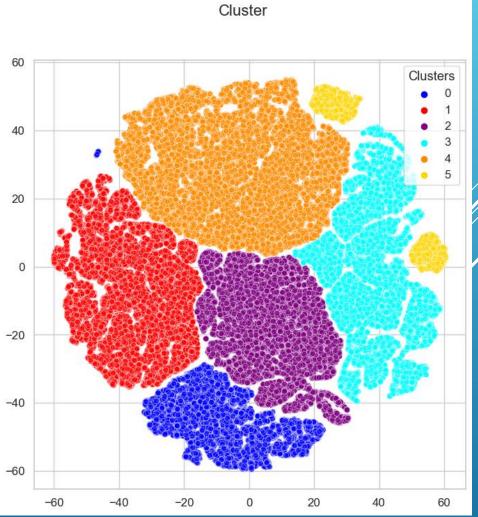


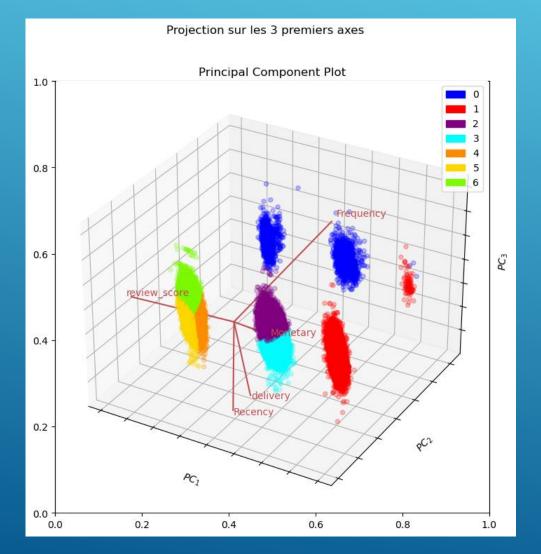
Visualisations 5 clusters





Visualisations 6 clusters





Visualisations 7 clusters

