Projet 4 : Anticipez les besoins en consommation électrique de bâtiments

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Sommaire

Introduction

Problématique

- Objectif de la ville de Seattle : atteindre la neutralité en émissions de carbone
- La ville s'intéresse aux émissions des batiments non destinés à l'habitation
- Pour cela des relevés de consommation ont été réalisés mais ils sont couteux à obtenir
- Est-il possible de prédire les émissions et de la consommation d'énergie pour des batiments pour lesquels les relevés n'ont pas été réalisé à partir des relevés déjà obtenus

Jeu de données

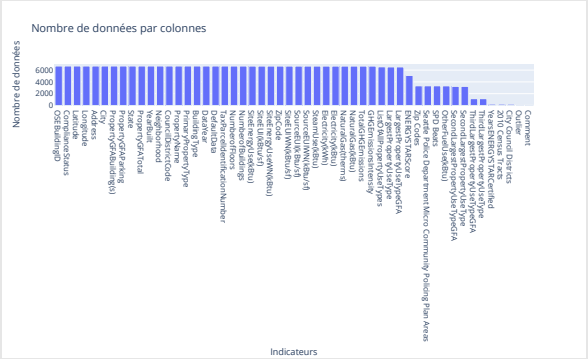
- Base de données issue de l'initiative de la ville de Seattle de proposer ses données en accès libre (Open Data)

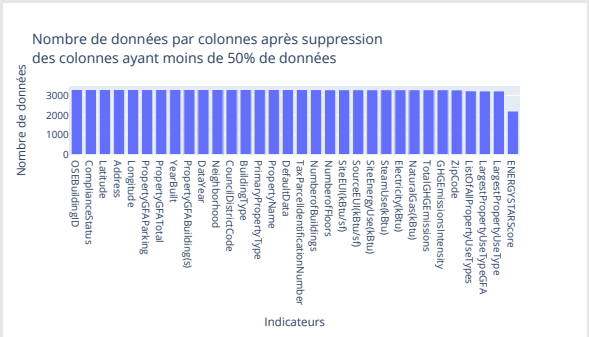
- Données concernant les batiments de la ville, caractérise :
  - le type,
  - la surface,
  - le nombre d'étages,
  - la consomation énergétique,
  - les émissions de carbone,
  - ⋮

- Données des années 2015 et 2016

Nettoyage du jeu de données

Nettoyage du jeu de données : Correction et selection des données





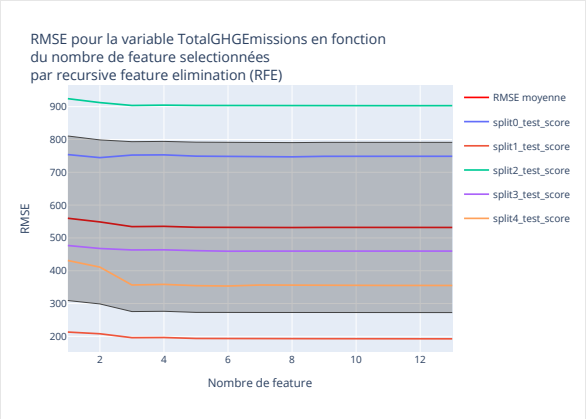
- Nettoyage des valeurs négative pour la surface des batiments/parkings, la consommation et les émissions
- Correction du nombre de d'étages aberrant pour certains batiments
- Correction du nombre de batiment nul par 1

- Conservation des variables ayant plus de 50% de données

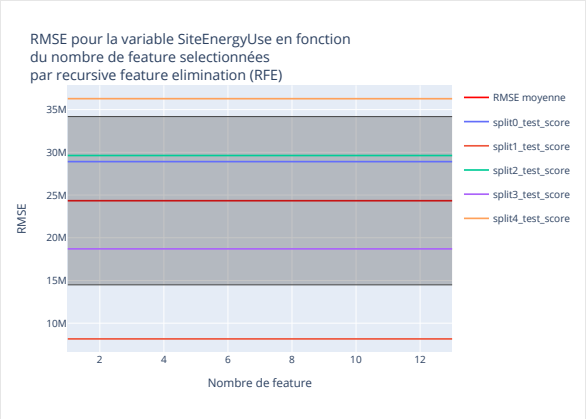
Nettoyage du jeu de données : Selections des variables

RFE et matrice de corrélation

Variables pertinentes pour les émissions



Variables pertinentes pour la consommation

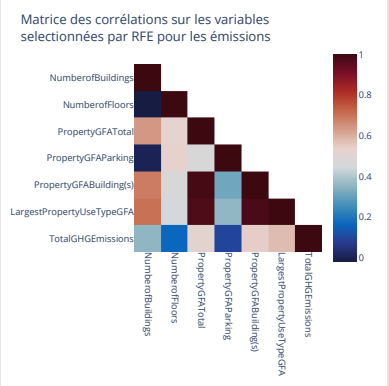


- Selection des variables les plus pertinentes par elimination recursive des variables (RFE)
- Réduction efficace pour les émissions
- Pas de réel changement de RMSE pour la consommation

Nettoyage du jeu de données : Selections des variables

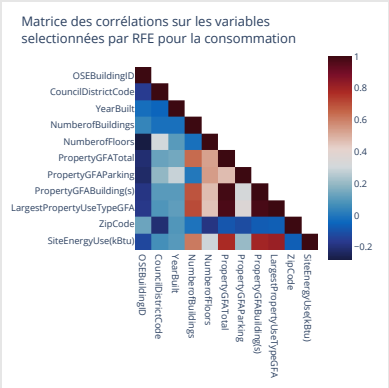
RFE et matrice de corrélation

Variables pertinentes pour les émissions



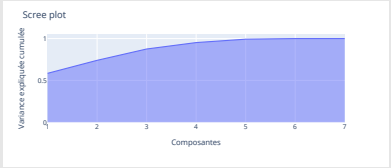
- Observation des résultats de RFE par les matrices de corrélation
- Les variables les plus corrélées sont communes aux deux sélection
- Conservation de 6 variables jugées pertinentes

Variables pertinentes pour la consommation

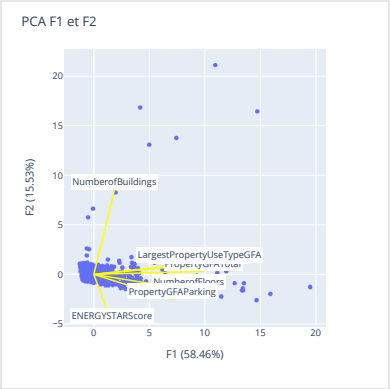


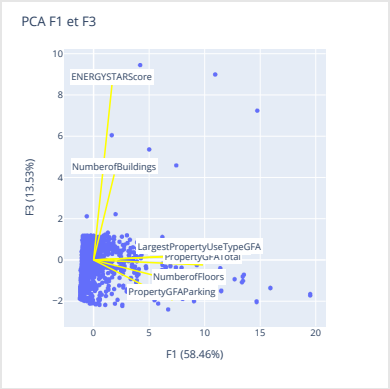
Nettoyage du jeu de données : Selections des variables

PCA



- Le graphique de la variance expliquée cumulée nous montre que 99% de la matrice est exliquée avec 5 variables
- Les quatres variables les plus corrélées se retrouvent sur l'axe F1
- L'EnergyStar score semble avoir une certaine importance car il explique une grande partie de l'axe F3





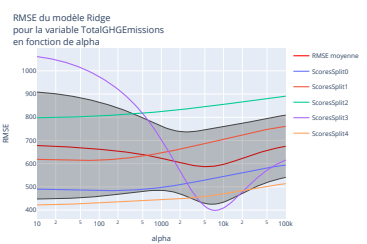
Étapes des modélisations

Étapes des modélisations

Modélisation émissions

Modèle Ridge

Variable non modifiée

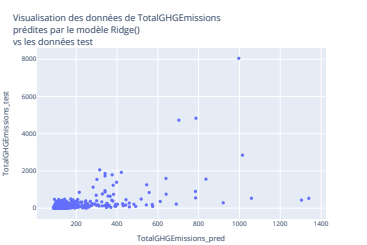


⇐

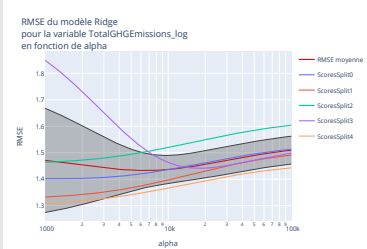
R^2	RMSE	MAE	MAE%	FitTime(s)
0.24	423.80	150.95	5.72	0.01

paramètre	Ridge()
alpha	5094.14

⇐



Variable au log

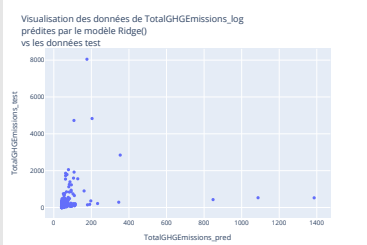


⇒

R^2	RMSE	MAE	MAE%	FitTime(s)
0.16	487.86	135.35	2.12	0.02

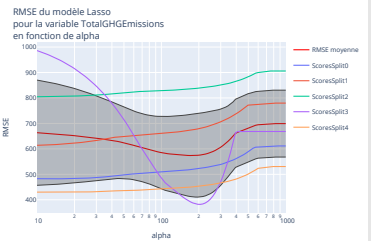
paramètre	Ridge()
alpha	6428.07

⇒



Modèle Lasso

Variable non modifiée

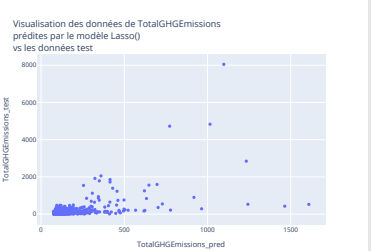


⇐

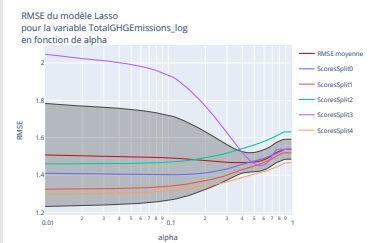
R^2	RMSE	MAE	MAE%	FitTime(s)
0.26	417.95	150.97	5.52	0.02

paramètre	Lasso()
alpha	178.86

⇐



Variable au log

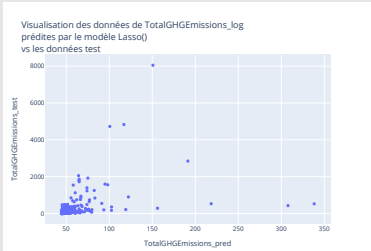


⇒

R^2	RMSE	MAE	MAE%	FitTime(s)
0.12	490.73	136.13	2.25	0.02

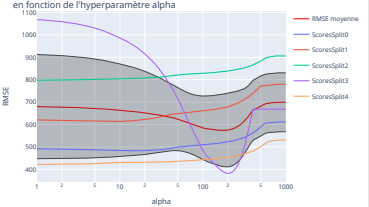
paramètre	Lasso()
alpha	0.34

⇒



Modèle ElasticNet

Variable non modifiée



⇐

R^2	RMSE	MAE	MAE%	FitTime(s)
0.26	417.53	150.73	5.48	0.01

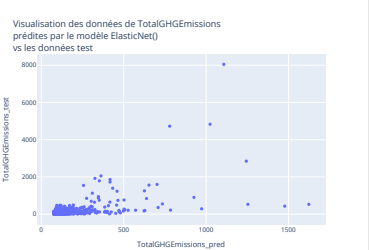
paramètre	ElasticNet()
alpha	174.75
l1_ratio	1.00

⇐ ⇒

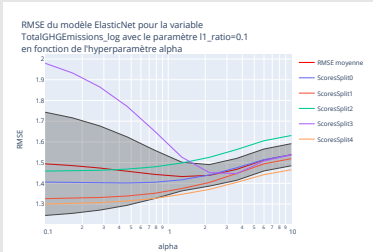
R^2	RMSE	MAE	MAE%	FitTime(s)
0.16	487.75	134.58	2.13	0.02

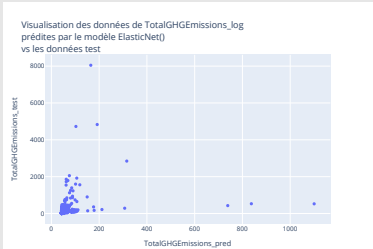
paramètre	ElasticNet()
alpha	1.29
l1_ratio	0.10

⇒



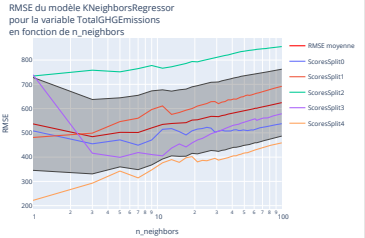
Variable au log





Modèle kNeighborsRegressor

Variable non modifiée



⇐

R^2	RMSE	MAE	MAE%	FitTime(s)
0.26	418.44	119.52	1.99	0.02

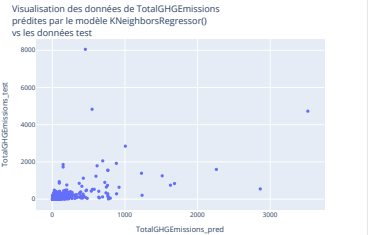
paramètre	KNeighborsRegressor()
n_neighbors	3

⇐ ⇒

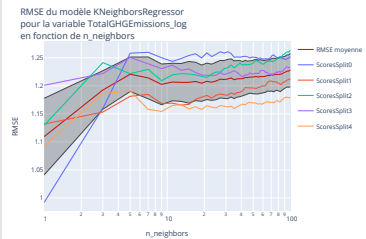
R^2	RMSE	MAE	MAE%	FitTime(s)
0.52	401.17	73.27	0.75	0.02

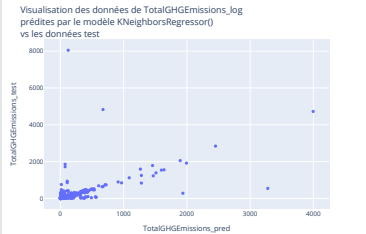
paramètre	KNeighborsRegressor()
n_neighbors	1

⇒



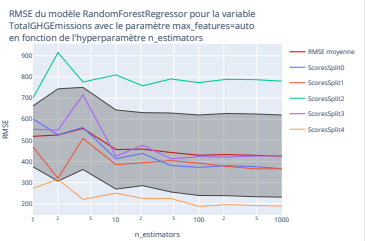
Variable au log

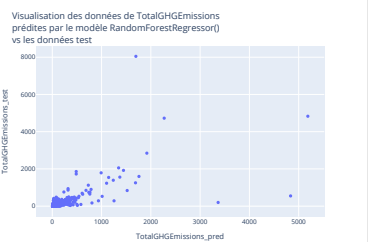




Modèle RandomForestRegressor

Variable non modifiée





⇐

R^2	RMSE	MAE	MAE%	FitTime(s)
0.42	371.52	89.73	1.44	11.48

paramètre	RandomForestRegressor()
n_estimators	1000
max_features	auto

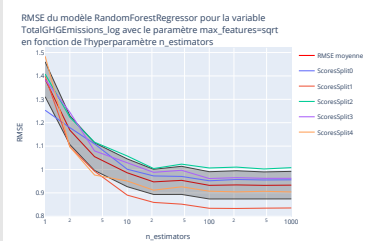
⇐ ⇒

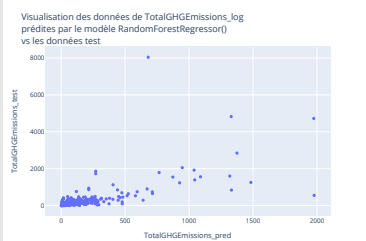
R^2	RMSE	MAE	MAE%	FitTime(s)
0.68	381.25	85.76	0.72	3.01

paramètre	RandomForestRegressor()
n_estimators	464
max_features	sqrt

⇒

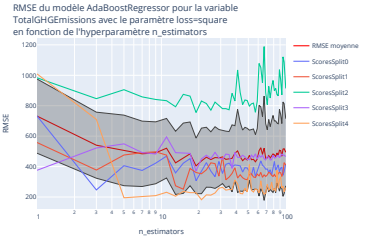
Variable au log





Modèle AdaBoostRegressor

Variable non modifiée



⇐

R^2	RMSE	MAE	MAE%	FitTime(s)
0.48	351.77	136.67	4.99	0.09

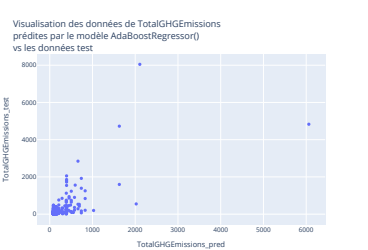
paramètre	AdaBoostRegressor()
n_estimators	19
loss	square

⇐ ⇒

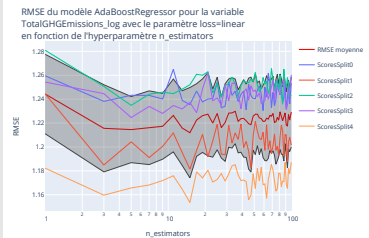
R^2	RMSE	MAE	MAE%	FitTime(s)
0.36	404.36	118.82	1.27	0.09

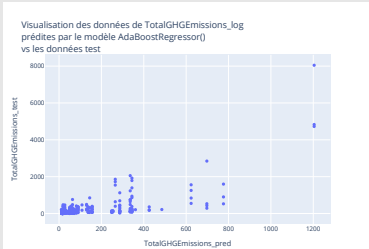
paramètre	AdaBoostRegressor()
n_estimators	15
loss	linear

⇒



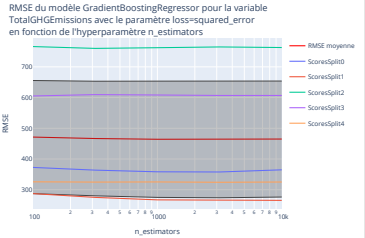
Variable au log





Modèle GradientBoostingRegressor

Variable non modifiée



⇐

R^2	RMSE	MAE	MAE%	FitTime(s)
0.47	355.84	74.99	1.34	10.37

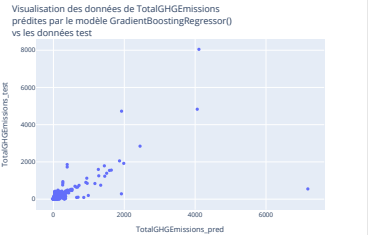
paramètre	GradientBoostingRegressor()
n_estimators	3162
loss	squared_error

⇐ ⇒

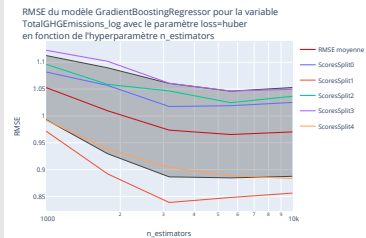
R^2	RMSE	MAE	MAE%	FitTime(s)
0.63	340.24	71.60	0.80	55.91

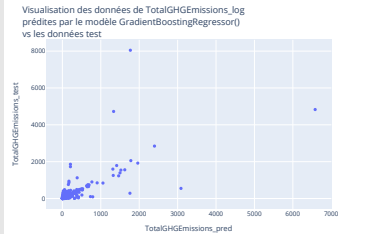
paramètre	GradientBoostingRegressor()
n_estimators	5623
loss	huber

⇒

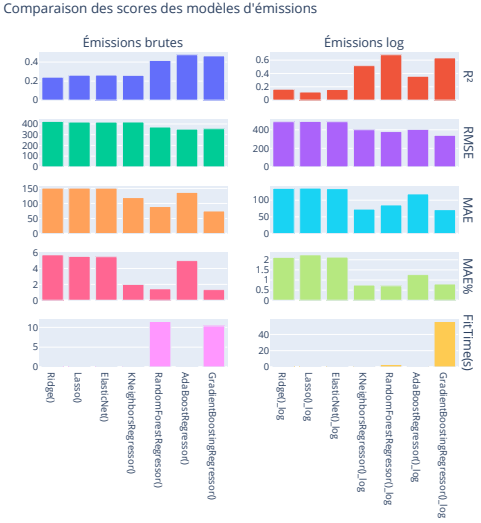


Variable au log





Comparaison des résultats selon que la variable est au log ou non



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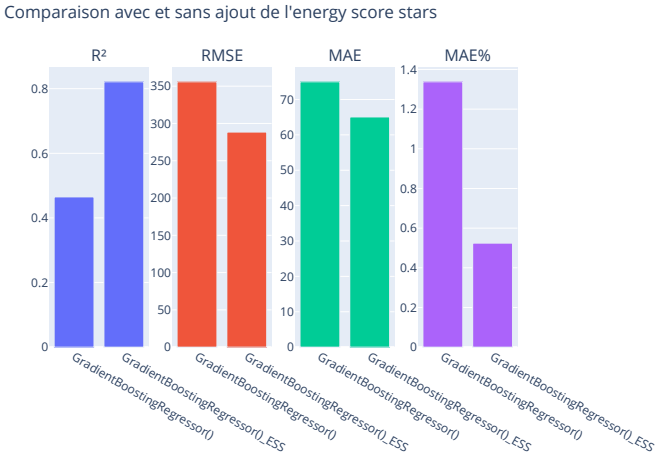
Influence de l'EnergyStar score sur la prédiction des Émissions



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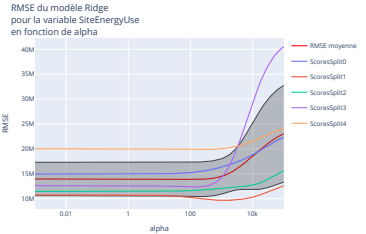
Modélisation consommation

Modèle Ridge

Variable non modifiée



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R^2	RMSE	MAE	MAE%	FitTime(
0.33	17660078.37	5153567.28	1.85	0.0

paramètre	Ridge()
alpha	102.35

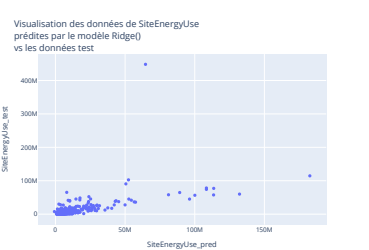
⇐

⇒

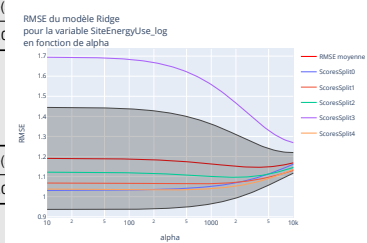
R^2	RMSE	MAE	MAE%	FitTime(
0.31	21043685.67	5666820.77	1.40	0.0

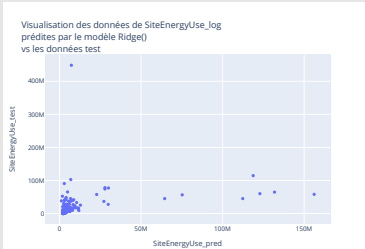
paramètre	Ridge()
alpha	3511.19

⇒



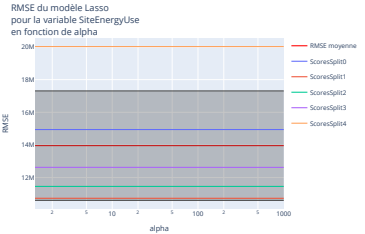
Variable au log

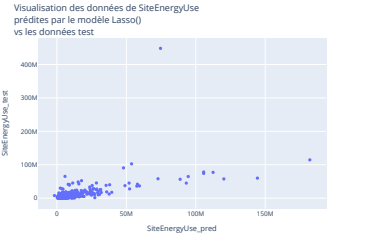




Modèle Lasso

Variable non modifiée





⇐

R^2	RMSE	MAE	MAE%	FitTime(
0.34	17499302.40	5269886.33	1.88	0.0

paramètre	Lasso()
alpha	1000.00

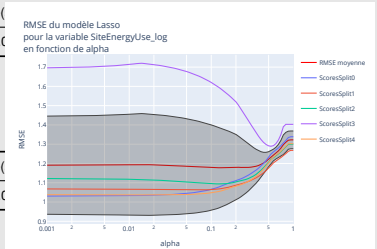
⇐ ⇒

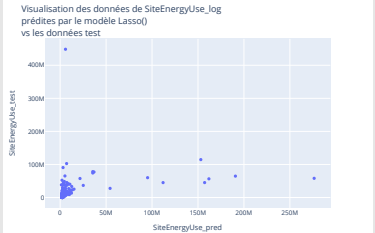
R^2	RMSE	MAE	MAE%	FitTime(
0.32	23496263.51	6175023.22	1.38	0.0

paramètre	Lasso()
alpha	0.12

⇒

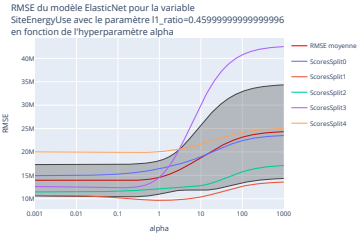
Variable au log





Modèle ElasticNet

Variable non modifiée



⇐

R^2	RMSE	MAE	MAE%	FitTime(
0.33	17669838.00	5135486.35	1.85	0.0

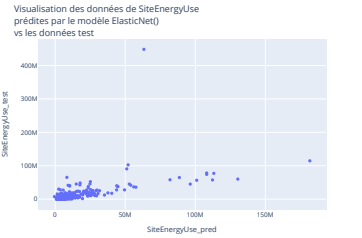
paramètre	ElasticNet()
alpha	0.09
l1_ratio	0.46

⇐ ⇒

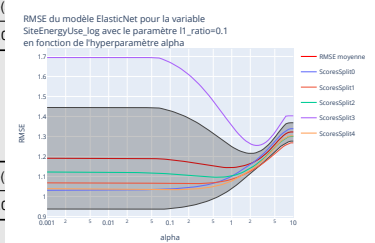
R^2	RMSE	MAE	MAE%	FitTime(
0.30	20734563.65	5593976.90	1.41	0.0

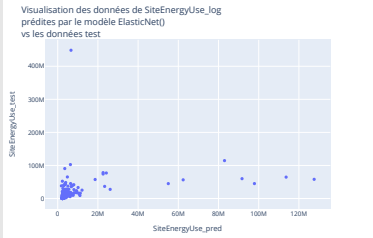
paramètre	ElasticNet()
alpha	0.89
l1_ratio	0.10

⇒



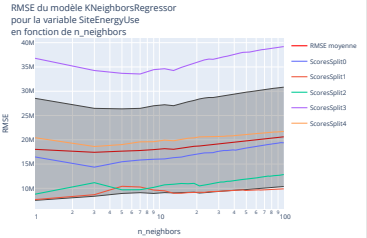
Variable au log

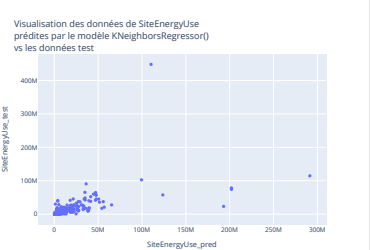




Modèle kNeighborsRegressor

Variable non modifiée





⇐

R^2	RMSE	MAE	MAE%	FitTime(
0.15	19891776.59	4958197.14	1.14	0.0

paramètre	KNeighborsRegressor()
n_neighbors	3

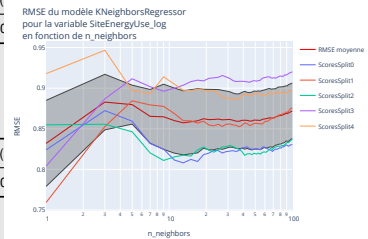
⇐ ⇒

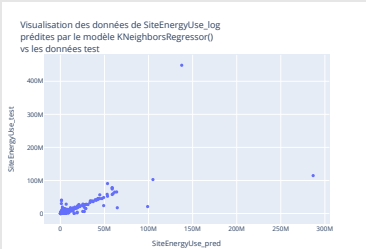
R^2	RMSE	MAE	MAE%	FitTime(
0.75	15125790.61	2521110.46	0.55	0.0

paramètre	KNeighborsRegressor()
n_neighbors	1

⇒

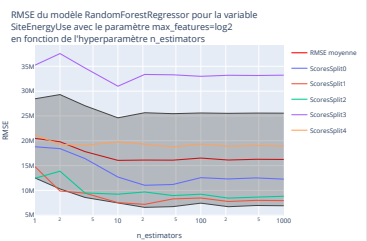
Variable au log





Modèle RandomForestRegressor

Variable non modifiée



R^2	RMSE	MAE	MAE%	FitTime(
0.43	16255496.44	3079266.36	0.85	0.0

paramètre	RandomForestRegressor()
n_estimators	10
max_features	log2

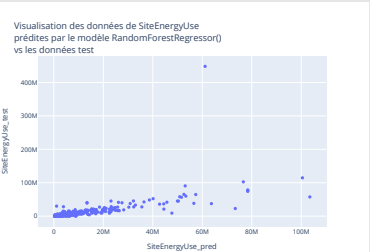
⇐

⇒

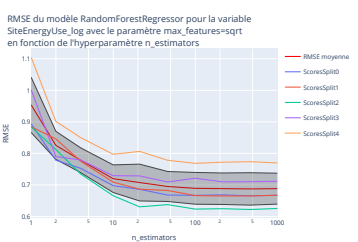
R^2	RMSE	MAE	MAE%	FitTime(
0.80	16533804.87	2771107.51	0.51	2.7

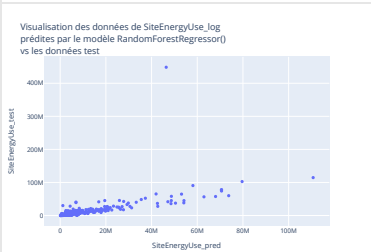
paramètre	RandomForestRegressor()
n_estimators	464
max_features	sqrt

⇒



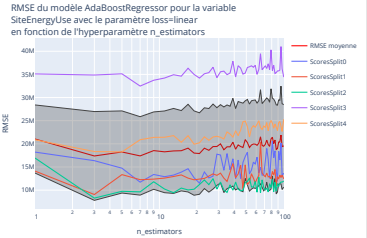
Variable au log

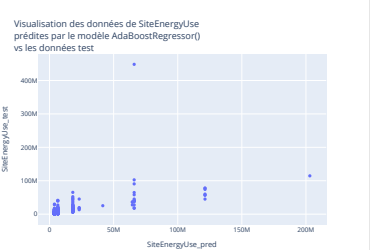




Modèle AdaBoostRegressor

Variable non modifiée





⇐

R^2	RMSE	MAE	MAE%	FitTime(
0.28	18239692.73	5482794.58	2.41	0.0

paramètre	AdaBoostRegressor()
n_estimators	3
loss	linear

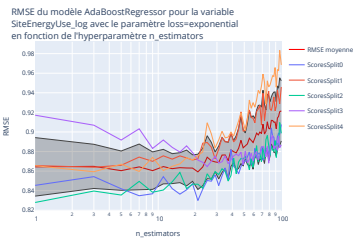
⇐ ⇒

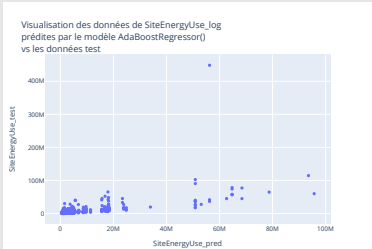
R^2	RMSE	MAE	MAE%	FitTime(
0.57	17101356.19	4203072.55	0.83	0.1

paramètre	AdaBoostRegressor()
n_estimators	21
loss	exponential

⇒

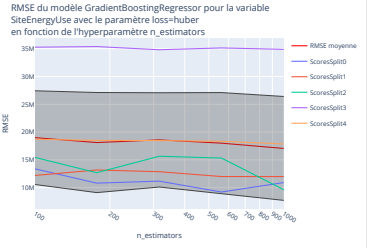
Variable au log





Modèle GradientBoostingRegressor

Variable non modifiée



⇐

R^2	RMSE	MAE	MAE%	FitTime(
0.43	16292946.43	2980171.79	0.90	7.9

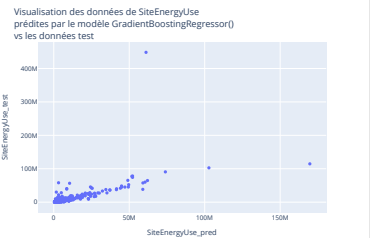
paramètre	GradientBoostingRegressor()
n_estimators	1000
loss	huber

⇐ ⇒

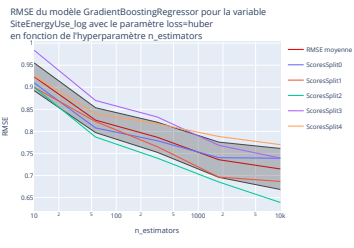
R^2	RMSE	MAE	MAE%	FitTime(
0.83	15038028.44	2135408.64	0.39	107.3

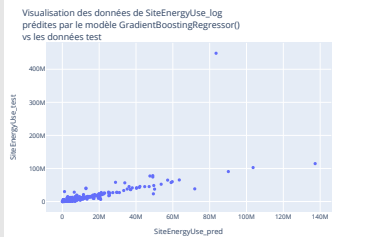
paramètre	GradientBoostingRegressor()
n_estimators	10000
loss	huber

⇒

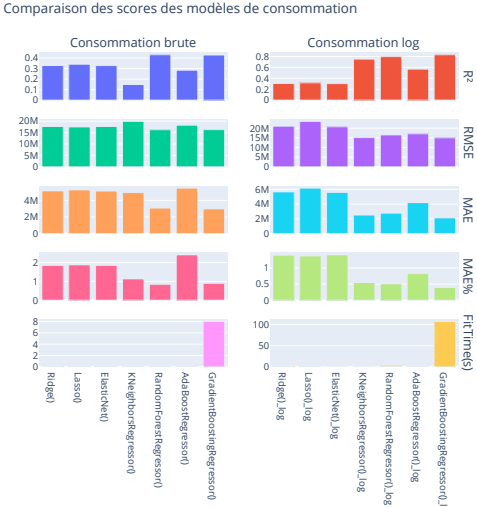


Variable au log





Comparaison des résultats selon que la variable est au log ou non



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Conclusion

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