

P4 PROJET ENERGIE SEATTLE VERTE 2050

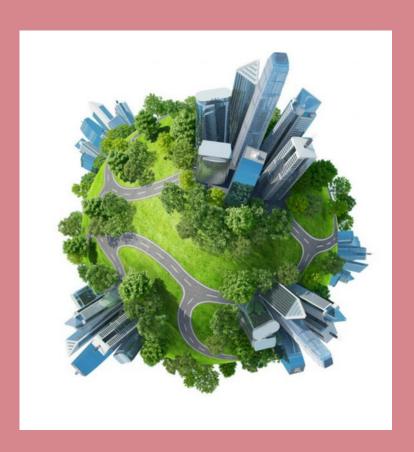
CATHERINE BRICE 15/11/2021
OPENCLASSROOMS
FORMATION DATA SCIENTIST

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INTRODUCTION

SEATTLE = ville neutre en émissions de carbone en 2050



PREDIRE:

Consommation énergétique de bâtiments non résidentiels 'SiteEnergyUse(kBtu)'

Emissions co2
'TotalGHGEmissions'

Modélisation ML supervisée à partir de 2 relevés 2015-2016 (gas, électricité, vapeur)

df_15.shape (3340, 42)

```
| df_15.sample()

OSEBuildingID DataYear BuildingType PrimaryPropertyType PropertyName TaxParcelldentificationNumber Locati

1031 20522 2015 NonResidential Non-Refrigerated WAREHOUSE 1498302235 '{"address":"20 21ST AVE S
```

df_16.shape (3376, 46)

]:	df_16.sample()										
	OSEBuildingID	DataYear	BuildingType	PrimaryPropertyType	PropertyName	Address	City	State	ZipCode	TaxParcelldentificationNumber	Cour
202	6 24179	2016	Multifamily LR (1-4)	Low-Rise Multifamily	Northbrook Place	10215 Lake City Way NE	Seattle	WA	98125.0	5101405948	
<											>

2 structures différentes entre relevé 2015 et relevé 2016

sur 2015 et pas 2016

['Location', 'OtherFuelUse(kBtu)', 'GHGEmissions(MetricTonsCO2e)', 'GHGEmissionsIntensity(kgCO2e/ft2)', 'Comment']

sur 2016 et pas 2015

['Address', 'City', 'State', 'ZipCode', 'Latitude', 'Longitude', 'Comments', 'TotalGHGEmissions', 'GHGEmissionsIntensity']

2015 : 3340 lignes, 42 features



2016 : 3376 lignes, 46 features



3318 lignes NonResidential, 46 features après nettoyage des données

float64

3308 non-null

				35	Steam
0	OSEBuildingID	3318 non-null	int64	36	Elect
1	DataYear	3318 non-null	int64	37	Elect
2	BuildingType	3318 non-null	object	38	Natur
3	PrimaryPropertyType	3318 non-null		39	Natur
4	PropertyName	3318 non-null	object	40	Defau
5	Address	3318 non-null		41	Comme
6	City	3318 non-null	object	42	Compl
7	State	3318 non-null	object	43	Outli
8	ZipCode	3302 non-null	object	44 45	Total GHGEm
9	TaxParcelIdentificationNumber	3317 non-null	object		es: fl
10	CouncilDistrictCode	3318 non-null	int64	1CVD	es. 11
11	Neighborhood	3318 non-null	object		
12	Latitude	3318 non-null	object		
13	Longitude	3318 non-null	object		
14	YearBuilt	3318 non-null	int64		
15		3316 non-null			
16		3310 non-null			
17		3318 non-null			
18	PropertyGFAParking	3318 non-null	int64		
19	PropertyGFABuilding(s)	3318 non-null	int64		
20	ListOfAllPropertyUseTypes	3255 non-null	object		
21	LargestPropertyUseType	3247 non-null	object		
22	LargestPropertyUseTypeGFA	3247 non-null	float64		
23	SecondLargestPropertyUseType	1667 non-null	object		
24	SecondLargestPropertyUseTypeGFA	1667 non-null	float64		
25	ThirdLargestPropertyUseType	684 non-null	object		
26	ThirdLargestPropertyUseTypeGFA	684 non-null	float64		
27	YearsENERGYSTARCertified	188 non-null	object		
28	ENERGYSTARScore	2211 non-null			
29		3308 non-null			
30	SiteEUIWN(kBtu/sf)	3308 non-null	float64		
31	SourceEUI(kBtu/sf)	3309 non-null	float64		
32		3309 non-null	float64		
33	SiteEnergyUse(kBtu)	3309 non-null	float64		

34 SiteEnergyUseWN(kBtu)

35	SteamUse(kBtu)	3309 non-null
36	Electricity(kWh)	3309 non-null
37	Electricity(kBtu)	3309 non-null
38	NaturalGas(therms)	3309 non-null
39	NaturalGas(kBtu)	3309 non-null
40	DefaultData	3317 non-null
41	Comments	12 non-null
42	ComplianceStatus	3318 non-null
43	Outlier	48 non-null
44	TotalGHGEmissions	3309 non-null
45	GHGEmissionsIntensity	3309 non-null
ltype	es: float64(19), int64(7),	object(20)



Décompactage de la variable Location
---> Latitude", "Longitude"

"Address", "City",

"State", "ZipCode"



Harmonisation (renommage) des noms de variables ('TotalGHGEmissions' et 'GHGEmissions(MetricTonsCO2e')

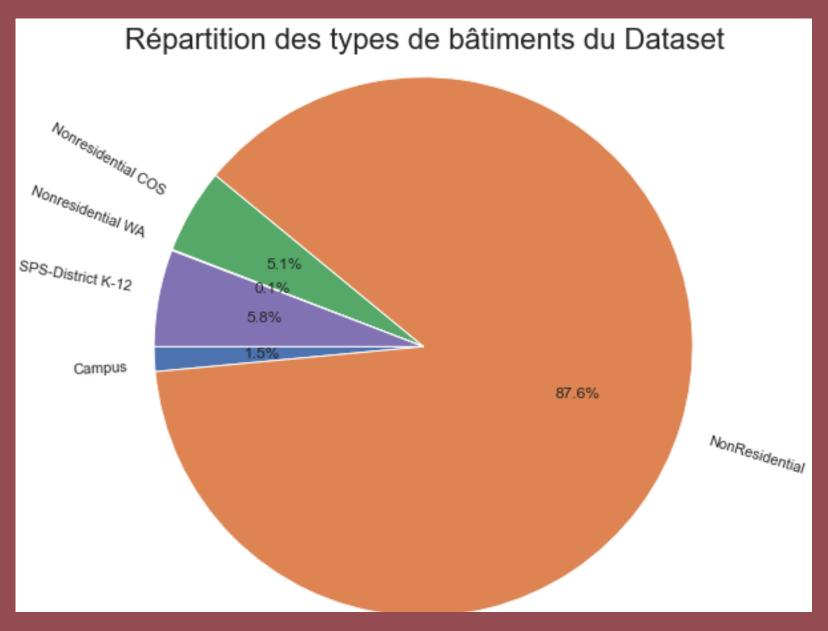


Suppression variables inutiles (Comments, Outliers, Year ENERGYSTARS corecertified), redondantes (consommations énergie...)

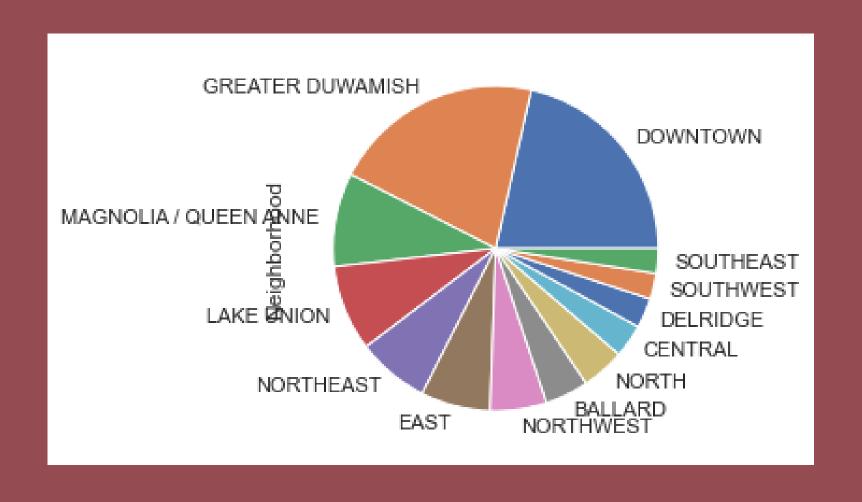


Suppression des valeurs manquantes ou pas remplies à 50% ListOfAllPropertyUseTypes, Largest..., Third...

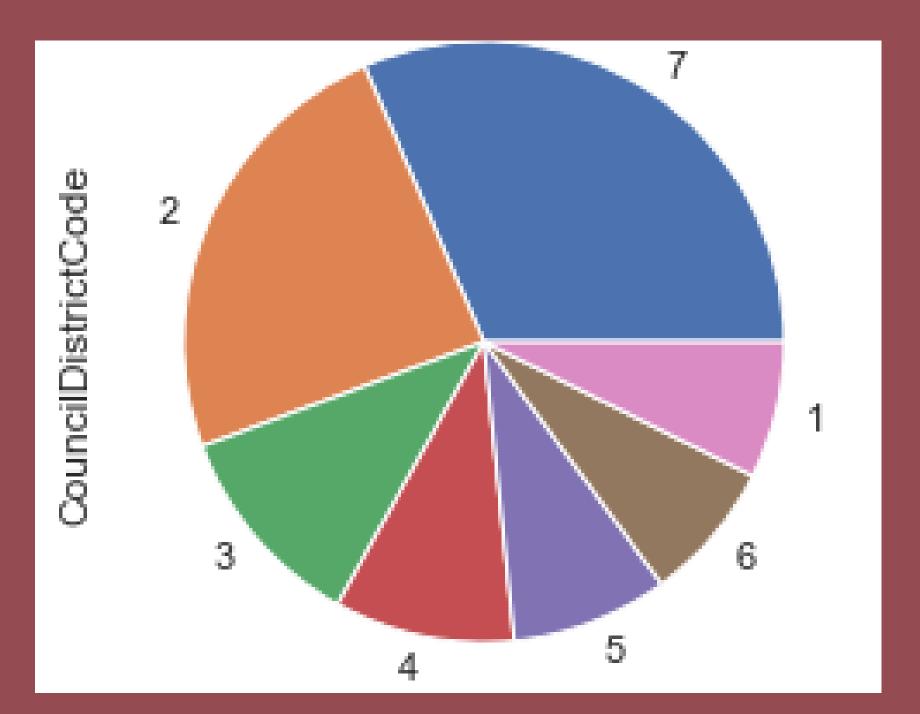
ANALYSE UNIVARIEE



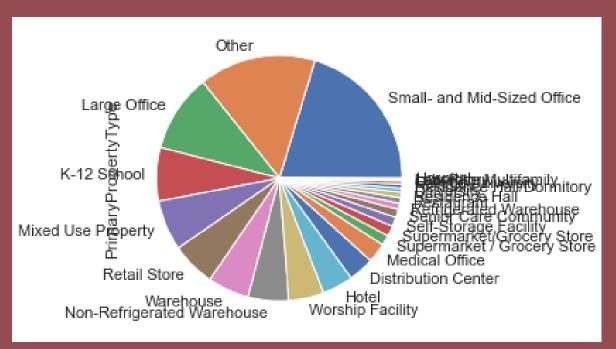
ANALYSE UNIVARIEE - 13 NEIGHBORHOODS



ANALYSE UNIVARIEE - CouncilDistrictCode

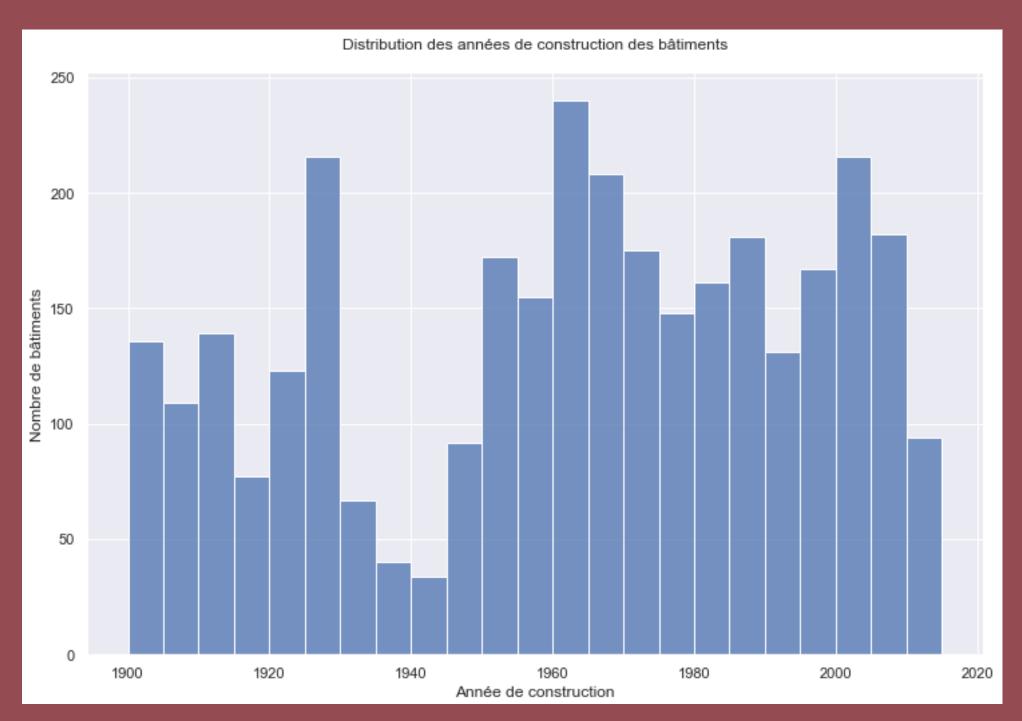


ANALYSE UNIVARIEE - primaryPropertyType

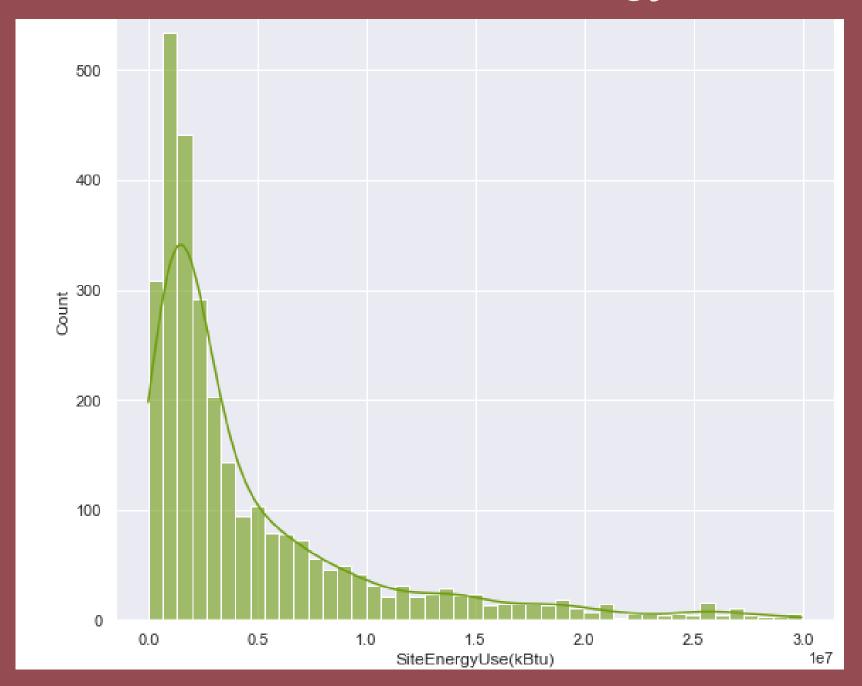


Small- and Mid-Sized Of	fice	571
Other	499	
Large Office	331	
K-12 School	267	7
Mixed Use Property	2	19
Warehouse	187	7
Non-Refrigerated Wareho	ouse	187
Retail Store	185	
Hotel	146	
Worship Facility	14	1
Distribution Center	10	06
Medical Office	82	2
Self-Storage Facility	!	56
Supermarket / Grocery S	Store	40
Senior Care Community		39
Supermarket/Grocery St	ore	36
Refrigerated Warehous	e	25
University	24	
Restaurant	23	
College/University	;	21
Residence Hall	2	1
Hospital	20	
Residence Hall/Dormite	ory	15
Laboratory	11	
Low-Rise Multifamily		4
SPS-District K-12	4	4
Office	3	
Name: PrimaryPropertyTy	pe, d	type:
int64		

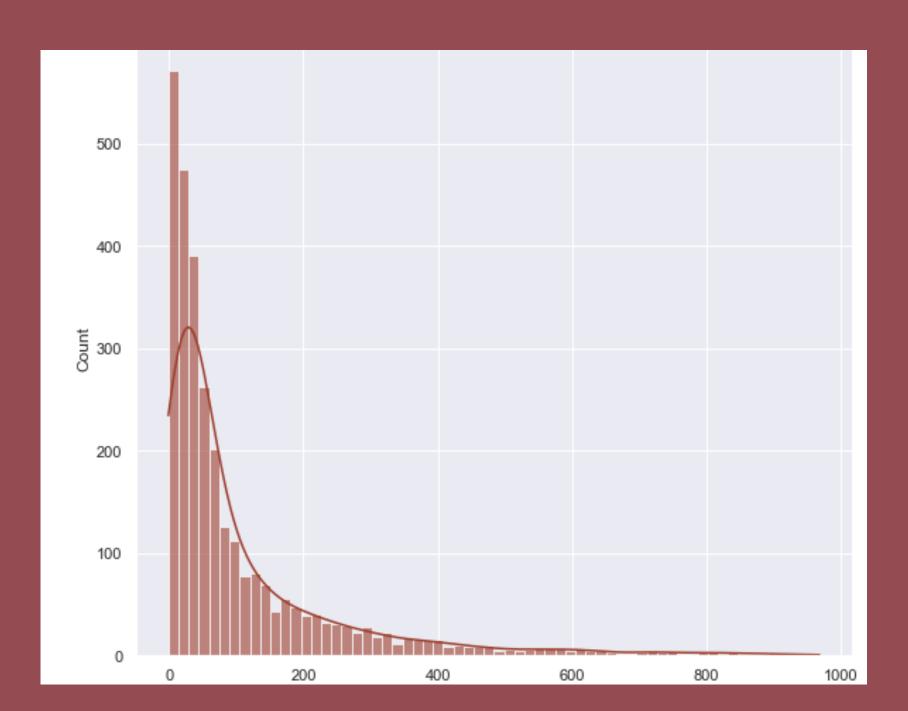
ANALYSE UNIVARIEE - ANNEES DE CONSTRUCTION



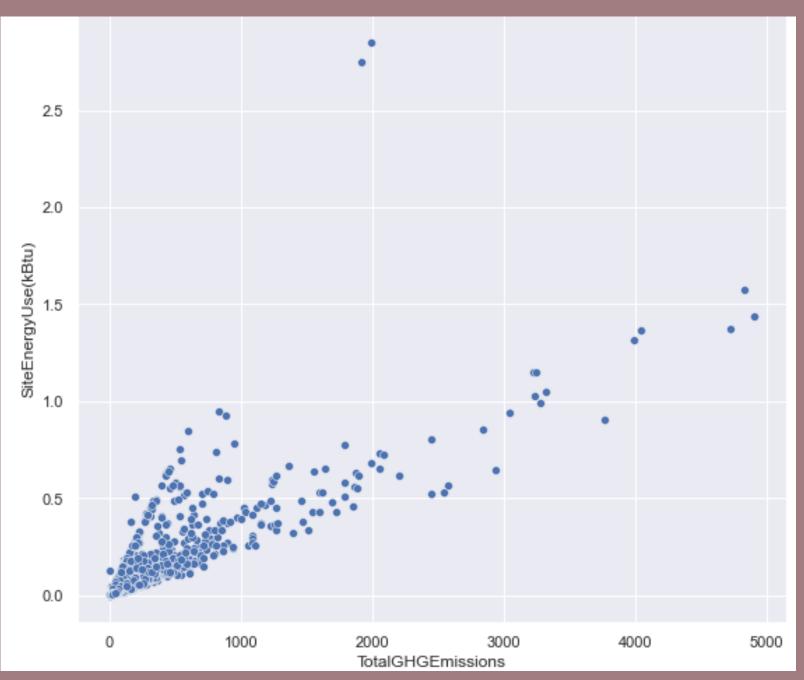
ANALYSE UNIVARIEE - SiteEnergyUse(kBtu)

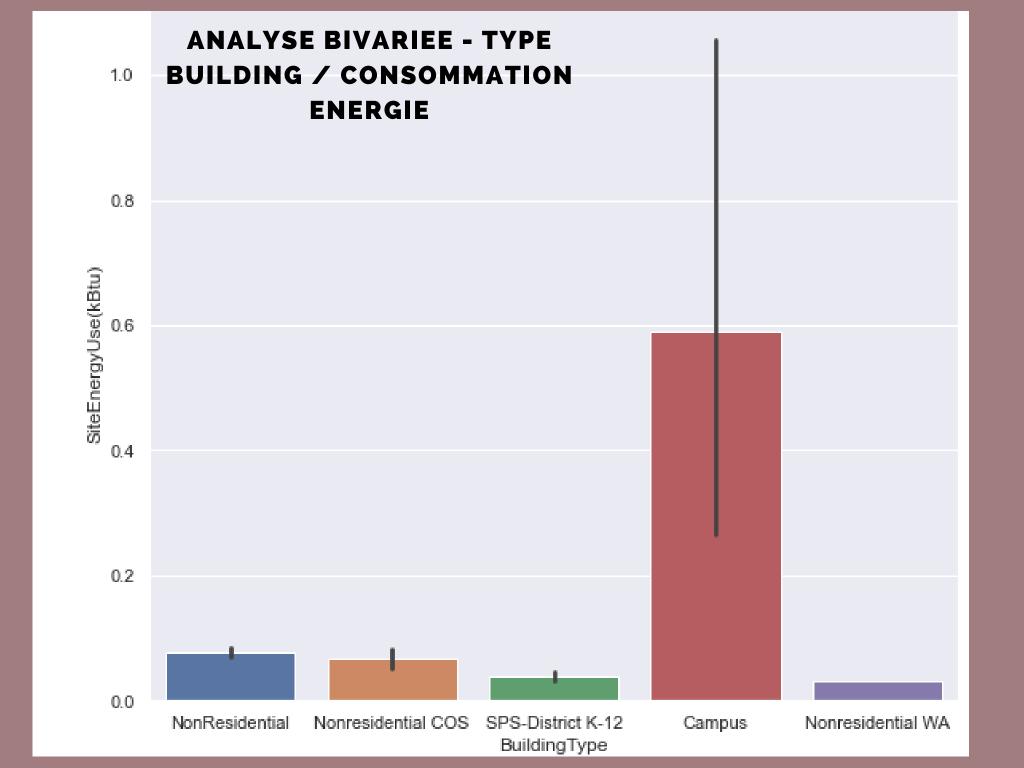


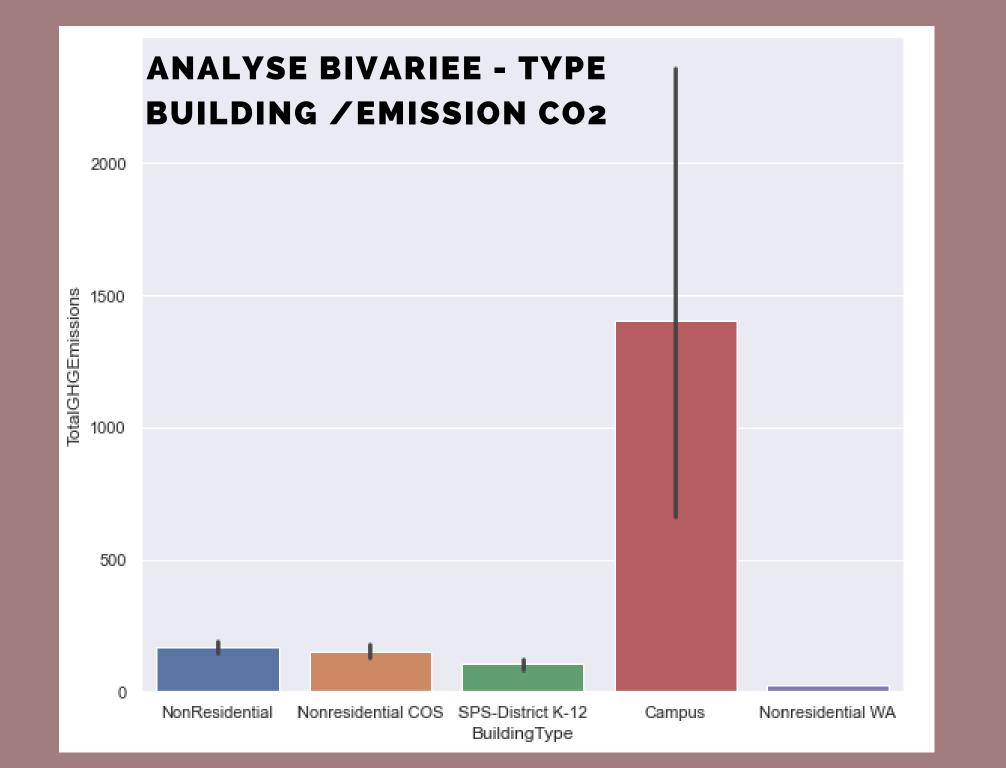
ANALYSE UNIVARIEE - EMISSIONS DE CO2



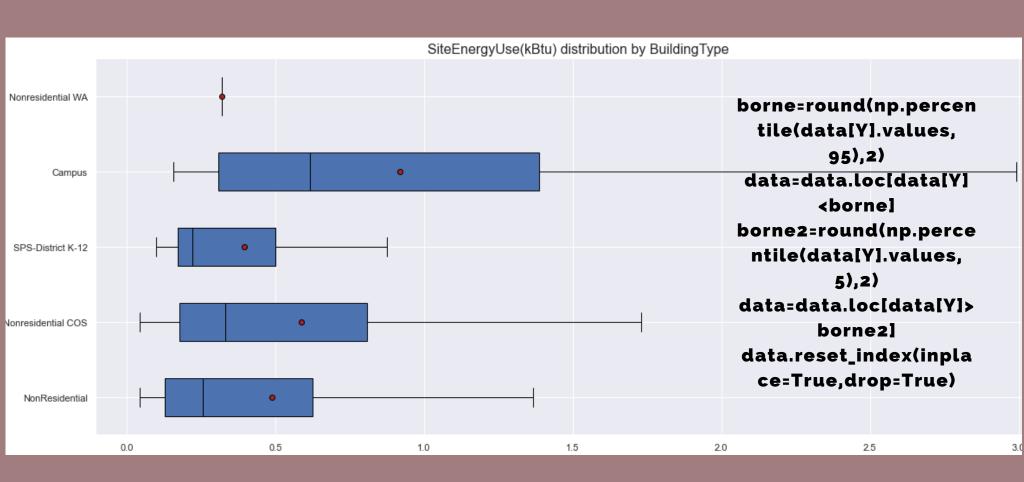
ANALYSE BIVARIEE - REPARTITION CONSOMMATION ENERGIE VS EMISSION CO2



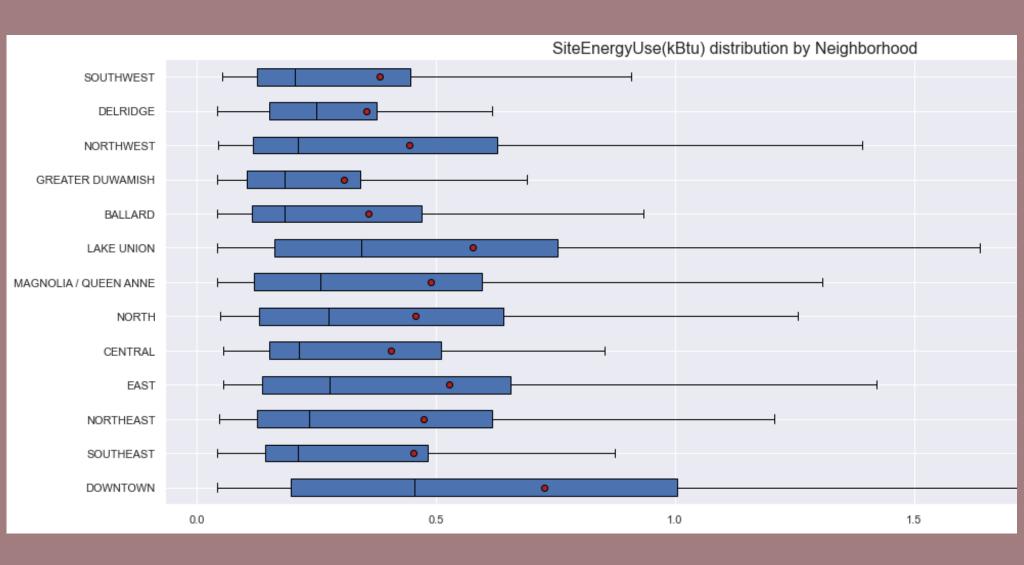




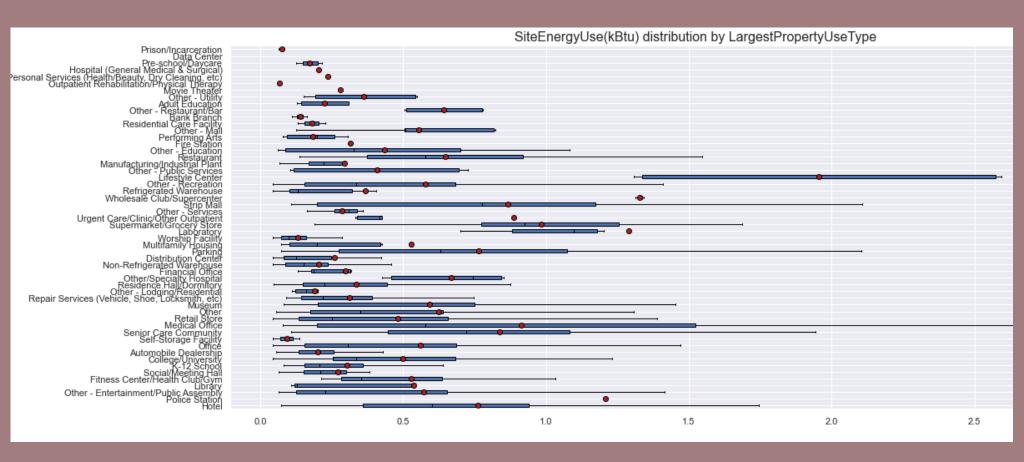
BOXPLOT - TYPE BUILDING / CONSOMMATION ENERGIE



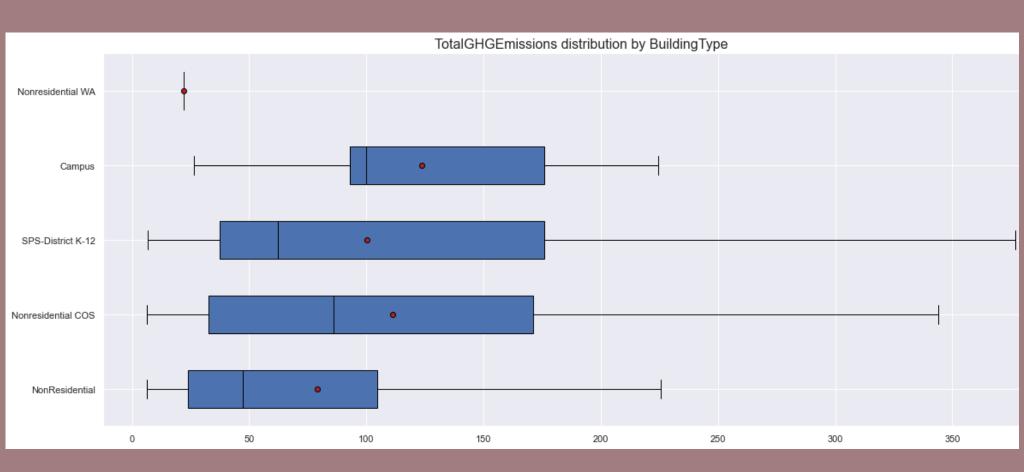
BOXPLOT - neighborhood/CONSOMMATION ENERGIE



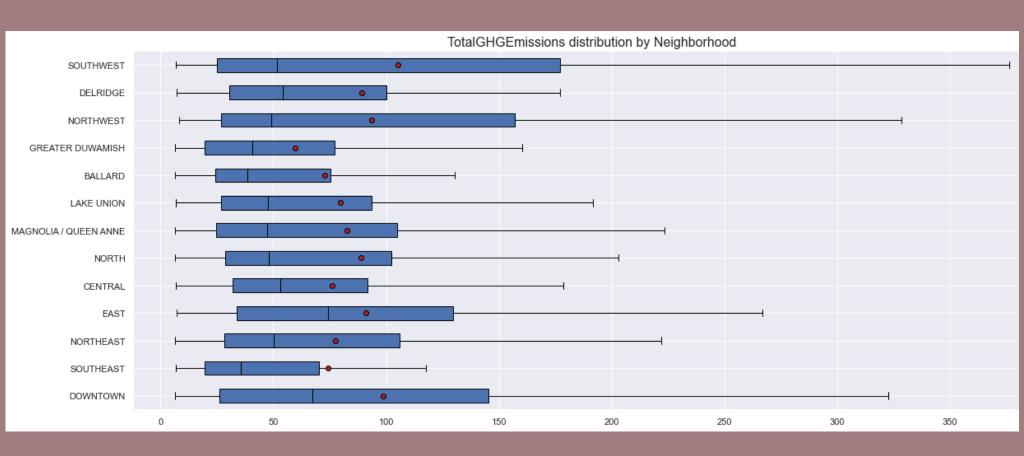
BOXPLOT - largestPropertyUseType/CONSOMMATION ENERGIE



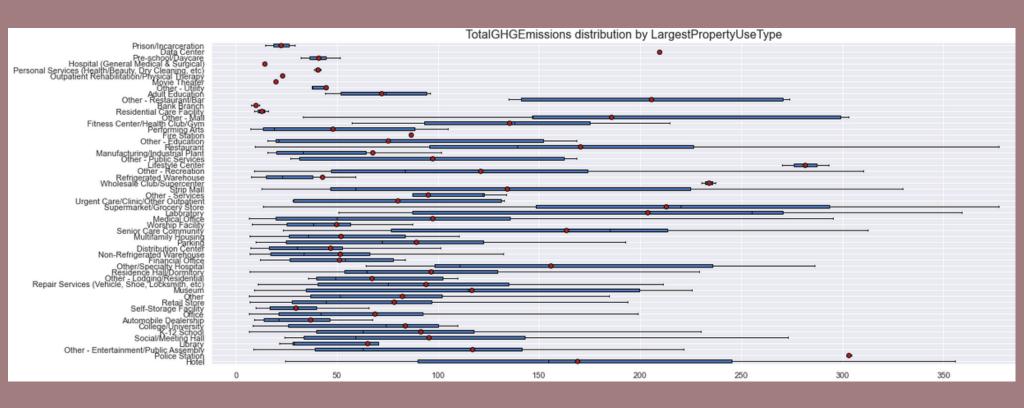
BOXPLOT - TYPE BUILDING / EMISSIONS CO2

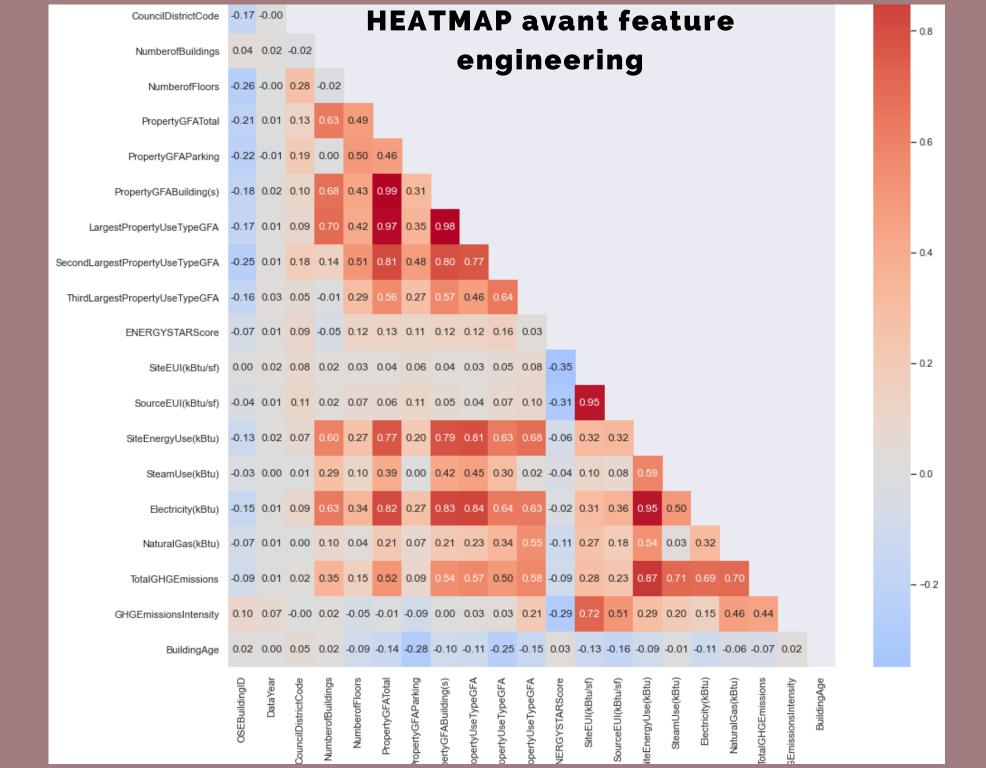


BOXPLOT - neighborhood/emissions co2



BOXPLOT - largestPropertyUseType/CONSOMMATION ENERGIE





FEATURE ENGINEERING

Conversion des différentes surfaces (Buildings et Parking) en pourcentage de la surface totale (GFABuildingRate, GFAParkingRate)

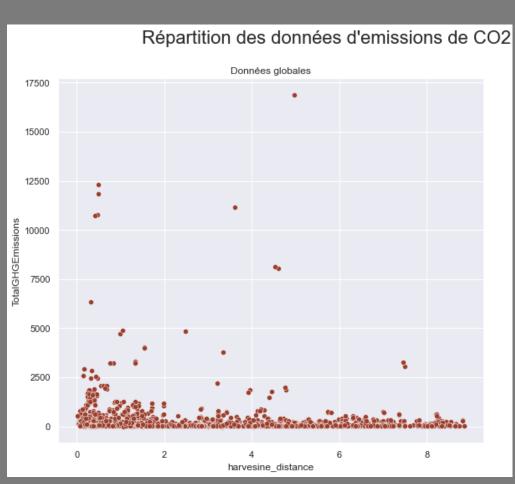
Calcul de la surface moyenne par bâtiment et par étage

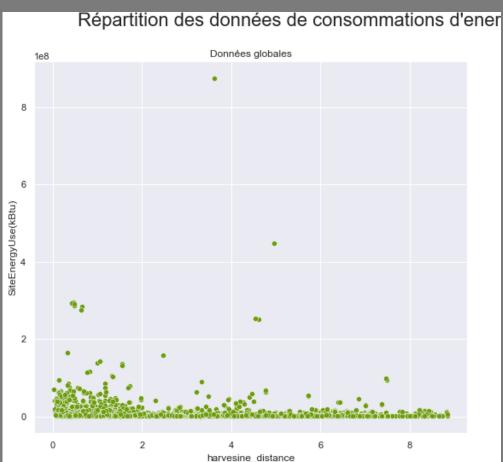
(GFAPerBuilding, GFAPerFloor)

	TotalUseTypeNumber	PropertyGFATotal	PropertyGFAParking	PropertyGFABuilding(s)	LargestPropertyUseTypeGFA
0	1	88434	0	88434	88434.0
1	3	103566	15064	88502	83880.0
2	3	961990	0	961990	757243.0
4	3	119890	12460	107430	123445.0
5	1	97288	37198	60090	88830.0
6	1	83008	0	83008	81352.0
7	1	102761	0	102761	102761.0
8	1	163984	0	163984	163984.0
10	1	153163	19279	133884	NaN
11	1	333176	61161	272015	336640.0

FEATURE ENGINEERING

Coordonnées géographiques (harvesine_distance) en fonction de la Latitude et Longitude et corrélation avec les targets





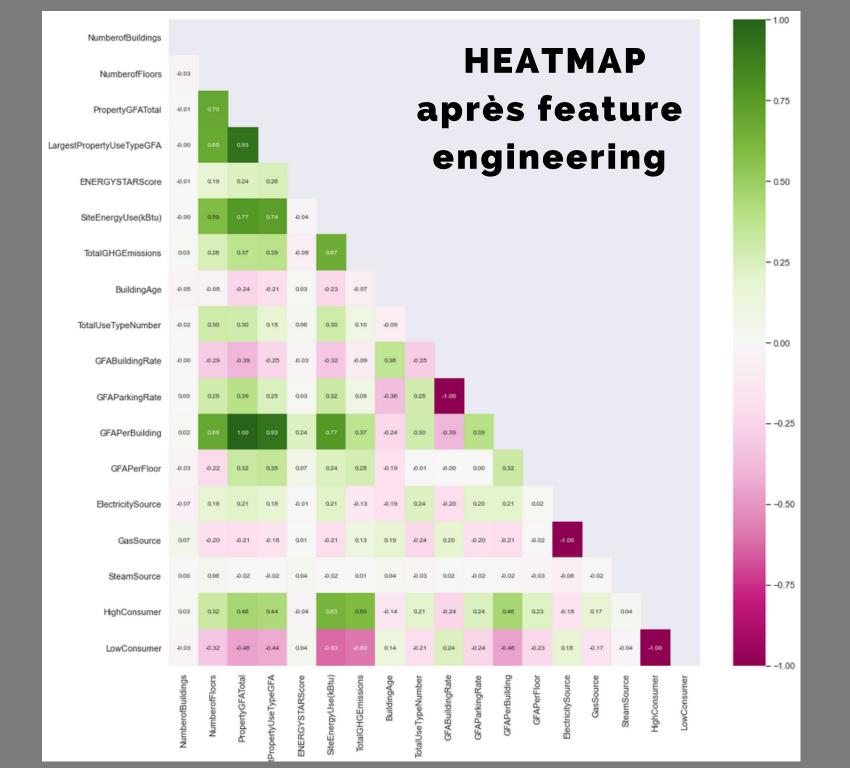
FEATURE ENGINEERING

supprimer 'LargestPropertyUseType' redondant avec 'PrimaryPropertyType'

'BuildingType' est de type NonResidential - on le retire pour la modélisation

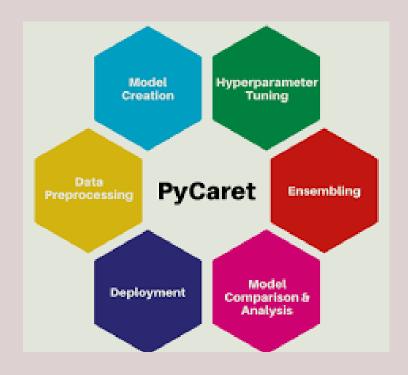
encoder les types object ['PrimaryPropertyType', 'CouncilDistrictCode', 'Neighborhood'

	PrimaryPropertyTypeOther	PrimaryPropertyTypeMixed Use Property	PrimaryPropertyTypeK-12 School	PrimaryPropertyTypeCollege/University	PrimaryPropertyTy and Mid-
0	1	0	0	0	
1	1	0	0	0	
2	0	1	0	0	
3	1	0	0	0	
4	0	1	0	0	



MODELISATION MACHINE LEARNING

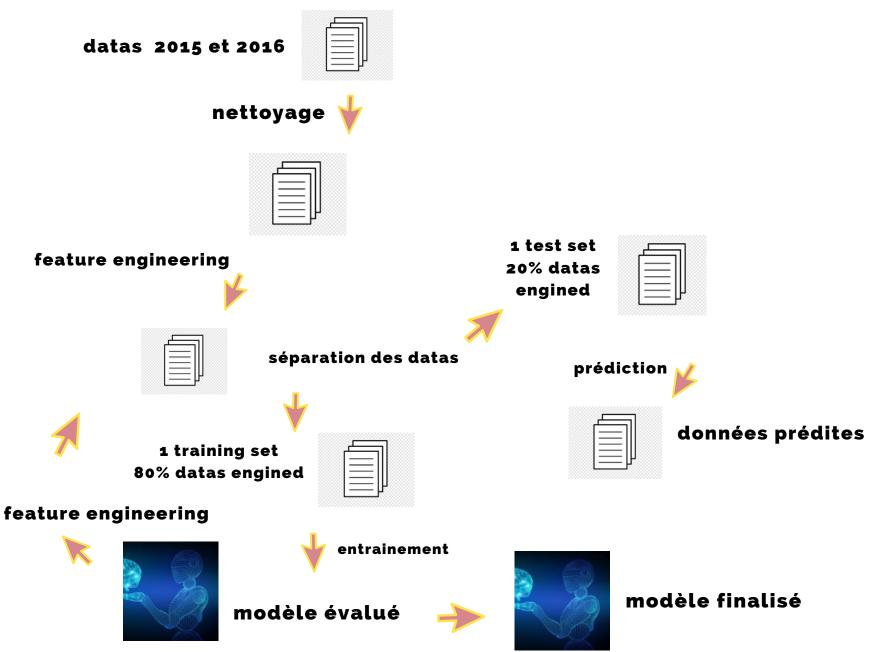




MODELISATION MACHINE LEARNING LE DATAFRAME

<class 'pandas.core.frame.DataFrame'> Int64Index: 1696 entries, 0 to 2500 Data columns (total 19 columns): # Column Non-Null Count Dtype O PrimaryPropertyType 1696 non-null object 1 CouncilDistrictCode 1696 non-null object Neighborhood 1696 non-null object NumberofBuildings 1696 non-null float64 NumberofFloors 1696 non-null float64 PropertyGFATotal 1696 non-null int64 LargestPropertyUseTypeGFA 1696 non-null float64 ENERGYSTARScore 1696 non-null float64 SiteEnergyUse(kBtu) 1696 non-null float64 TotalGHGEmissions 1696 non-null float64 1696 non-null int64 10 BuildingAge 11 TotalUseTypeNumber 1696 non-null int64 1696 non-null float64 12 GFABuildingRate 1696 non-null float64 13 GFAParkingRate 14 GFAPerBuilding 1696 non-null float64 15 GFAPerFloor 1696 non-null float64 16 ElectricitySource 1696 non-null int64 17 GasSource 1696 non-null int64 18 SteamSource 1696 non-null int64 dtypes: float64(10), int64(6), object(3) memory usage: 265.0+ KB

MODELISATION MACHINE LEARNING PROCESS



Prediction target 'SiteEnergyUse(kBtu)'

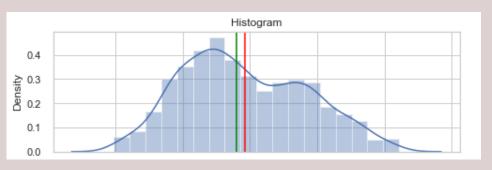
Echantillon Site_Energy_Use

	Model					
et	Extra Trees Regressor	Sans pas	sage au log	j	avec passage au log	
		R2	RMSLE		R2	RMSLE
Cross validation 10 folds		0.8881	0.3020		0.8883	0.0190
ol	odele tuné (avec ptimisation des	0.8433	0.4099		0.7738	0.0273
	perparamètres) ctions unseen data	0.7794	0.4650		0.7564	0.0296

Skewness of the SiteEnergyUse(kBtu) is 2.1100300655712854

1e-7 Histogram 2 0 0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5 SiteEnergyUse(kBtu) 1e-7

Skewness of the SiteEnergyUse(kBtu) is 0.2817765168279764



hyperparamètres

sans passage au Log et avec passage au Log

bootstrap	False
ccp_alpha	0.0
criterion	mse
max_depth	10
max_features	1.0
max_leaf_nodes	None
max_samples	None
min_impurity_decrease	0.4
min_impurity_split	None
min_samples_leaf	3
min_samples_split	10
min_weight_fraction_leaf	0.0
n_estimators	70
n_jobs	-1
oob_score	False
random_state	3213
verbose	0
warm_start	False

	Parameters
bootstrap	False
ccp_alpha	0.0
criterion	mse
max_depth	7
max_features	1.0
max_leaf_nodes	None
max_samples	None
min_impurity_decrease	0.001
min_impurity_split	None
min_samples_leaf	5
min_samples_split	5
min_weight_fraction_leaf	0.0
n_estimators	80
n_jobs	-1
oob_score	False
random_state	6929
verbose	0
warm_start	False

Prediction target TotalGHGEmissions (avec ENERGYSTARScore)

Echantillon



Sans passage au log

avec passage au log

Cross	validation	10
	folds	

R2	RMSLE	R2	RMSLE
0.7023	0.5107	0.7415	0.1067

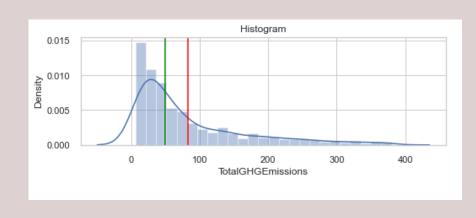
modele tuné (avec optimisation des hyperparamètres) 0.6123 0.6437

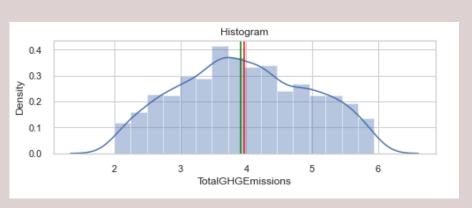
0.4076 0.1609

prédictions unseen data

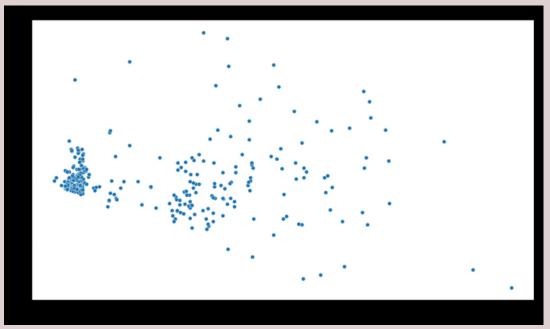
0.6154 0.6654

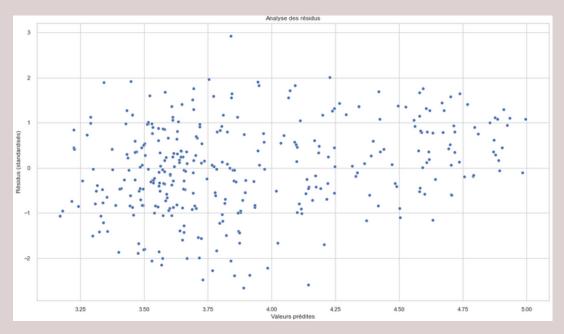
0.4319 0.1515



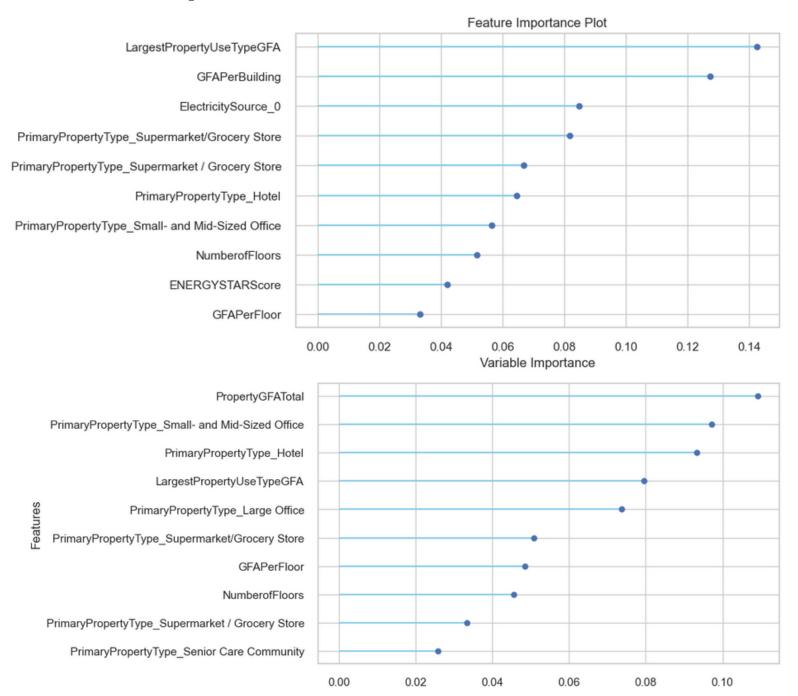


Analyse des résidus sans passage au Log et avec passage au Log





Feature importance sans passage au Log et avec passage au Log



hyperparamètres sans passage au Log et avec passage au Log

	Parameters
bootstrap	True
ccp_alpha	0.0
criterion	mse
max_depth	11
max_features	1.0
max_leaf_nodes	None
max_samples	None
min_impurity_decrease	0.0005
min_impurity_split	None
min_samples_leaf	2
min_samples_split	9
min_weight_fraction_leaf	0.0
n_estimators	290
n_jobs	-1
oob_score	False
random_state	7001
verbose	0
warm_start	False

	Parameters
bootstrap	False
ccp_alpha	0.0
criterion	mae
max_depth	11
max_features	log2
max_leaf_nodes	None
max_samples	None
min_impurity_decrease	0
min_impurity_split	None
min_samples_leaf	3
min_samples_split	2
min_weight_fraction_leaf	0.0
n_estimators	200
n_jobs	-1
oob_score	False
random_state	2167
verbose	0
warm_start	False

Prediction target TotalGHGEmissions (sans ENERGYSTARScore)

Echantillon

	Model
et	Extra Trees Regressor

Sans passage au log

avec passage au log

Cross validation 10 folds

R2 RMSLE R2 RMSLE 0.6508 0.6320 0.1242

modele tuné (avec optimisation des hyperparamètres) 0.5303 0.7036

0.3962 0.

0.1602

prédictions unseen data

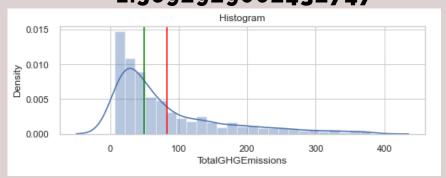
0.6317

0.6598

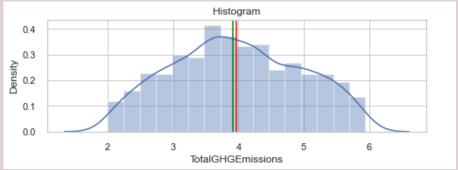
0.4105

0.1663

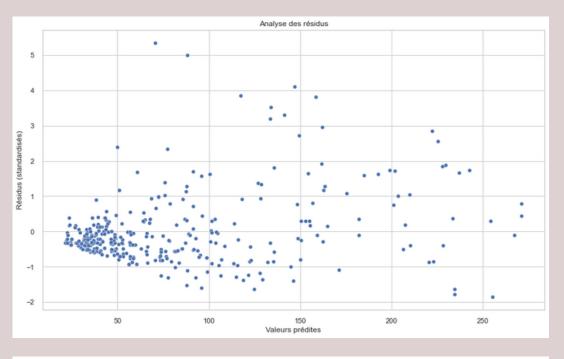
Skewness of TotalGHGEmissions is 1.5692929002432747

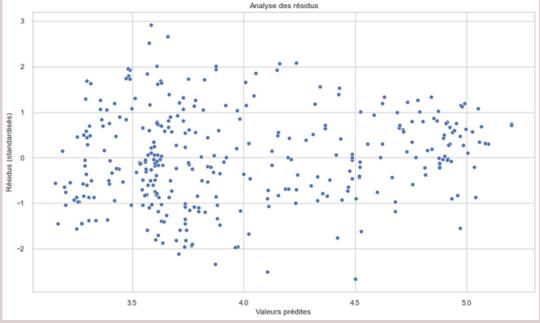


Skewness of TotalGHGEmissions is 0.05692164562813998

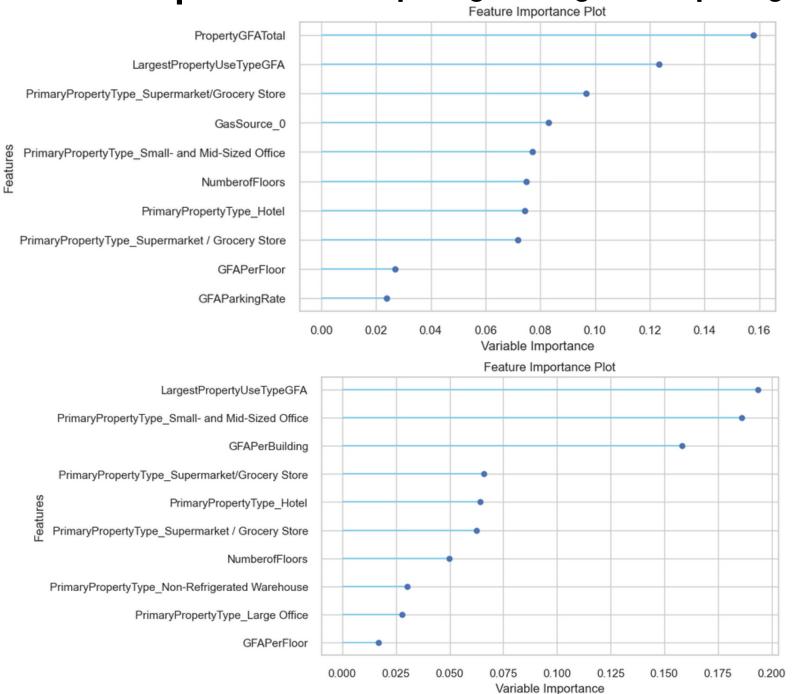


Analyse des résidus sans passage au Log et avec passage au Log





Feature importance sans passage au Log et avec passage au Log



hyperparamètres sans passage au Log et avec passage au Log

	Parameters
bootstrap	False
ccp_alpha	0.0
criterion	mse
max_depth	8
max_features	1.0
max_leaf_nodes	None
max_samples	None
min_impurity_decrease	0.01
min_impurity_split	None
min_samples_leaf	3
min_samples_split	10
min_weight_fraction_leaf	0.0
n_estimators	280
n_jobs	-1
oob_score	False
random_state	3483
verbose	0
warm_start	False

	Parameters
bootstrap	True
ccp_alpha	0.0
criterion	mae
max_depth	5
max_features	1.0
max_leaf_nodes	None
max_samples	None
min_impurity_decrease	0.002
min_impurity_split	None
min_samples_leaf	2
min_samples_split	9
min_weight_fraction_leaf	0.0
n_estimators	250
n_jobs	-1
oob_score	False
random_state	7632
verbose	0
warm_start	False

CONCLUSION

Prédiction consommation énergie : modèle en surapprentissage qui n'a rien appris. Le passage au log diminue le RMSLE

Prédiction émissions de CO2: ENERGYstarscore n'apporte pas une grande plus value. Les modèles avec et sans cette variable sont sensiblement les mêmes en terme de performances et erreurs.

Par rapport à ce jeu de données, les passages au log diminuent le RMSLE mais n'améliorent pas beaucoup les prédictions.

On pourrait revoir les features et les recombiner pour trouver des axes d'amélioration.