Aliza Muslimah PYTN-07 **Assignment 1** Preprocessing In [1]: # Import Libraries import math import statistics import numpy as np import scipy.stats import pandas as pd import matplotlib.pyplot as plt import datetime import string from sklearn.impute import KNNImputer import statsmodels.api as sm import seaborn as sns %matplotlib inline import warnings warnings.filterwarnings("ignore") In [2]: # Membaca Dataset df_nyc = pd.read_csv('nyc-rolling-sales.csv.zip', skipinitialspace=True) Out[2]: **TAX BUILDING BUILDING CLASS** EASE-RESIDENTIAL COMM **BOROUGH NEIGHBORHOOD CLASS BLOCK LOT CLASS AT** ADDRESS ... **MENT AT UNITS PRESENT CATEGORY PRESENT** 07 RENTALS -0 ALPHABET CITY 2A 392 6 5 WALKUP NaN **AVENUE B APARTMENTS** 07 RENTALS -**234 EAST** 5 ALPHABET CITY WALKUP 2 399 26 C7 4TH 28 NaN **APARTMENTS** STREET 07 RENTALS -197 EAST 2 6 1 ALPHABET CITY 2 399 39 C7 3RD 16 WALKUP NaN **STREET APARTMENTS** 07 RENTALS -**154 EAST** 3 7 **ALPHABET CITY** 2B 402 21 7TH 10 WALKUP NaN **APARTMENTS** STREET 07 RENTALS -**301 EAST** 8 **ALPHABET CITY** 2A 404 55 C2 10TH 6 WALKUP NaN **APARTMENTS STREET 02 TWO** 37 QUAIL 8409 5 WOODROW 2 84543 **FAMILY** 7349 34 NaN LANE **DWELLINGS** 02 TWO 32 84544 WOODROW 2 8410 **FAMILY** PHEASANT 7349 78 NaN **DWELLINGS** LANF 02 TWO B2 49 PITNEY 8411 5 WOODROW 84545 1 7351 60 FAMILY NaN AVENUE ... DWELLINGS 2730 22 STORE ARTHUR ... WOODROW 4 7100 28 84546 8412 BUILDINGS KILL ROAD 35 INDOOR **PUBLIC AND** 155 CLAY 4 7105 679 WOODROW 0 84547 8413 NaN PIT ROAD ... CULTURAL **FACILITIES** 84548 rows × 22 columns In [3]: df nyc.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 84548 entries, 0 to 84547 Data columns (total 22 columns): # Column Non-Null Count Dtype 0 Unnamed: 0 84548 non-null int64 1 BOROUGH 84548 non-null int64 84548 non-null object 84548 non-null object 83810 non-null object 84548 non-null int64 2 NEIGHBORHOOD 3 BUILDING CLASS CATEGORY 4 TAX CLASS AT PRESENT 5 BLOCK 6 LOT 84548 non-null int64

 6
 LOT
 84548 non-null int64

 7
 EASE-MENT
 0 non-null float64

 8
 BUILDING CLASS AT PRESENT
 83810 non-null object

 9
 ADDRESS
 84548 non-null object

 10
 APARTMENT NUMBER
 19052 non-null object

 11
 ZIP CODE
 84548 non-null int64

 12
 RESIDENTIAL UNITS
 84548 non-null int64

 13
 COMMERCIAL UNITS
 84548 non-null int64

 14
 TOTAL UNITS
 84548 non-null object

 16
 GROSS SQUARE FEET
 84548 non-null object

 16
 GROSS SQUARE FEET
 84548 non-null int64

 17
 YEAR BUILT
 84548 non-null int64

 17 YEAR BUILT 84548 non-null int64
18 TAX CLASS AT TIME OF SALE 84548 non-null int64 19 BUILDING CLASS AT TIME OF SALE 84548 non-null object 84548 non-null object 20 SALE PRICE 21 SALE DATE 84548 non-null object dtypes: float64(1), int64(10), object(11) memory usage: 14.2+ MB In [4]: def check_missing_value(a): print(a.isnull().sum().sort_values(ascending=False)) check_missing_value(df_nyc) EASE-MENT APARTMENT NUMBER TAX CLASS AT PRESENT BUILDING CLASS AT PRESENT 738 Unnamed: 0 COMMERCIAL UNITS SALE PRICE BUILDING CLASS AT TIME OF SALE TAX CLASS AT TIME OF SALE YEAR BUILT GROSS SQUARE FEET LAND SQUARE FEET TOTAL UNITS ZIP CODE RESIDENTIAL UNITS BOROUGH ADDRESS LOT BUILDING CLASS CATEGORY NEIGHBORHOOD 0 SALE DATE dtype: int64 In [5]: #Menghapus kolom yang tidak diperlukan no = ['Unnamed: 0', 'EASE-MENT', 'ADDRESS', 'APARTMENT NUMBER', 'ZIP CODE'] df nyc.drop(no, axis=1, inplace=True) In [6]: #Mengubah Tipe Kolom #Tipe kolom 'SALE PRICE' harus numerik dan missing value akan di-replace dengan NaN df_nyc['SALE PRICE'] = pd.to_numeric(df_nyc['SALE PRICE'], errors='coerce') # Tipe kolom 'LAND SQUARE FEET' dan 'GROSS SQUARE FEET' harus numerik df_nyc['LAND SQUARE FEET'] = pd.to_numeric(df_nyc['LAND SQUARE FEET'], errors='coerce') df_nyc['GROSS SQUARE FEET'] = pd.to_numeric(df_nyc['GROSS SQUARE FEET'], errors='coerce') # Tipe kolom 'SALE DATE' harus datetime df_nyc['SALE DATE'] = pd.to_datetime(df_nyc['SALE DATE'], errors='coerce') # Tipe kolom dibawah harus caregorical categorical = ['NEIGHBORHOOD', 'BUILDING CLASS CATEGORY', 'TAX CLASS AT PRESENT', 'BUILDING CLASS AT PRESENT', 'BUILDING CLASS AT TIME OF SALE', 'TAX CLASS AT TIME OF SALE'] for col in categorical: df_nyc[col] = df_nyc[col].astype('category') In [7]: df nyc.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 84548 entries, 0 to 84547 Data columns (total 17 columns): # Column Non-Null Count Dtype 84548 non-null int64 BOROUGH NEIGHBORHOOD 84548 non-null category 84548 non-null category BUILDING CLASS CATEGORY 83810 non-null category TAX CLASS AT PRESENT BLOCK 84548 non-null int64 84548 non-null int64 BUILDING CLASS AT PRESENT 83810 non-null category
RESIDENTIAL UNITS 84548 non-null int64 84548 non-null int64 COMMERCIAL UNITS 84548 non-null int64 58296 non-null float64 56936 non-null float64 TOTAL UNITS 10 LAND SQUARE FEET 11 GROSS SQUARE FEET 12 YEAR BUILT 84548 non-null int64
13 TAX CLASS AT TIME OF SALE 84548 non-null category 14 BUILDING CLASS AT TIME OF SALE 84548 non-null category 69987 non-null float64 16 SALE DATE 84548 non-null datetime64[ns] dtypes: category(6), datetime64[ns](1), float64(3), int64(7) memory usage: 7.8 MB In [8]: df nyc Out[8]: TAX BUILDING BUILDING LAND GROSS **CLASS** RESIDENTIAL COMMERCIAL TOTAL BLOCK LOT CLASS AT **BOROUGH NEIGHBORHOOD CLASS SQUARE SQUARE** AT UNITS **UNITS UNITS** CATEGORY **PRESENT** FEET **FEET PRESENT** 07 RENTALS -C2 ALPHABET CITY WALKUP 2A 392 1633.0 6440.0 **APARTMENTS** 07 RENTALS -28 **ALPHABET CITY** WALKUP 399 26 C7 31 4616.0 18690.0 **APARTMENTS** 07 RENTALS -C7 16 2212.0 7803.0 ALPHABET CITY WALKUP 399 39 17 **APARTMENTS** 07 RENTALS -**ALPHABET CITY** 21 10 0 6794.0 3 1 WALKUP 2B 402 C4 10 2272.0 **APARTMENTS** 07 RENTALS -6 0 1 **ALPHABET CITY** 2A 404 55 C2 6 2369.0 WALKUP 4615.0 **APARTMENTS** 02 TWO 5 84543 WOODROW 0 2400.0 2575.0 **FAMILY** 7349 34 В9 **DWELLINGS** 02 TWO 5 WOODROW 2 84544 **FAMILY** 7349 78 В9 2 0 2498.0 2377.0 **DWELLINGS** 02 TWO 5 WOODROW 60 В2 0 2 4000.0 1496.0 84545 **FAMILY** 7351 **DWELLINGS** 22 STORE 5 84546 WOODROW 7100 28 Κ6 7 208033.0 64117.0 **BUILDINGS** 35 INDOOR **PUBLIC AND** 5 WOODROW 0 84547 7105 679 P9 10796.0 2400.0 **CULTURAL FACILITIES** 84548 rows × 17 columns In [9]: # Cek data duplikat sum(df nyc.duplicated()) Out[9]: In [10]: # Hapus data duplikat df nyc = df nyc.drop duplicates(df nyc.columns, keep='last') In [11]: sum(df_nyc.duplicated()) Out[11]: In [12]: # Menghilangkan value yang berisi null df_nyc = df_nyc[df_nyc['LAND SQUARE FEET'].notnull()] df_nyc = df_nyc[df_nyc['GROSS SQUARE FEET'].notnull()] df_nyc = df_nyc[df_nyc['SALE PRICE'].notnull()] In [13]: #Melihat distribusi data plt.figure(figsize=(12,5)) sns.displot(df nyc['SALE PRICE'], bins=40, rug=True) plt.show() <Figure size 864x360 with 0 Axes> 50000 40000 30000 20000 10000 0.5 0.0 1.0 2.0 SALE PRICE In [14]: #Menghilangkan outliers $df_n = df_nyc[(df_nyc['SALE PRICE'] > 10000) & (df_nyc['SALE PRICE'] < 10000000)]$ plt.figure(figsize=(12,5)) sns.displot(df_n['SALE PRICE'], bins=40, rug=True) plt.show() <Figure size 864x360 with 0 Axes> 10000 8000 6000 4000 2000 0.0 1.0 le7 SALE PRICE In [15]: # Mengubah nilai'SALE PRICE' ke nilai lognya df_n['LOG_PRICE'] = np.log(df_n['SALE PRICE']) sns.displot(df_n['LOG_PRICE'], bins=100) <seaborn.axisgrid.FacetGrid at 0x2d77a62ad30> Out[15]: 1600 1400 1200 1000 800 600 400 200 0 13 LOG_PRICE df_n['LOG_PRICE'].describe() count 36181.000000 Out[16]: 13.323709 mean 0.840553 std 9.210440 min 12.900656 13.321214 13.760918 75% 16.118096 max Name: LOG_PRICE, dtype: float64 Data sudah berdistribusi normal sehingga data siap digunakan In [17]: # plot kurva dengan boxplot untuk melihat tampilan lain dari data plt.figure(figsize=(10,6)) sns.boxplot(x='LOG_PRICE', data = df_n) plt.ticklabel_format(style='plain', axis='x') plt.title("Boxplot dari Harga Jual (USD)") plt.show() Boxplot dari Harga Jual (USD) 15 16 LOG_PRICE **Measure of Central Tendency: Mean** In [18]: # Mencari nilai Mean dari kolom 'SALE PRICE' mean = df_n['LOG_PRICE'].mean() print('Mean : ', mean) Mean: 13.323709361183091 **Measure of Central Tendency: Median** In [19]: # Mencari nilai Median dari kolom 'SALE PRICE' median = df n['LOG PRICE'].median() print('Median : ', median) Median : 13.321214236149494 **Measure of Central Tendency: Modus** In [20]: # Mencari nilai Modus dari kolom 'YEAR BUILT' tahun_pembuatan = df_nyc['YEAR BUILT'].value_counts() tahun_pembuatan 4471 Out[20]: 1930 3683 1925 3387 2871 1910 2606 1889 1875 1829 1891 1851 Name: YEAR BUILT, Length: 151, dtype: int64 Diketahui bahwa modus dari 'YEAR BUILT' adalah tahun 1920 Measure of Spread : Range In [21]: # Mencari Range dari kolom 'YEAR BUILT' maxi = tahun_pembuatan.max() print('Nilai maximal : ', maxi) mini = tahun_pembuatan.min() print('Nilai minimal : ', mini) range = maxi - mini print('Range : ', range) Nilai maximal: 4471 Nilai minimal: 1 Range : 4470 Measure of Spread : Variance In [22]: # Mencari variance dari kolom 'SALE PRICE' variance = df n['LOG PRICE'].var() print('Variance : ', variance) Variance: 0.7065287124016151 **Measure of Spread: Standard Deviation** In [23]: # Mencari standard deviation dari kolom 'SALE PRICE' std = np.sqrt(variance) print('Standard Deviation : ', std) Standard Deviation : 0.8405526232197572 In [24]: # Cara lain std1 = df n['LOG PRICE'].std() print('Standard Deviation : ', std1) Standard Deviation : 0.8405526232197572 **Probability Distribution** In [25]: # Import Libraries %matplotlib inline import matplotlib.pyplot as plt from IPython.display import Math, Latex from IPython.core.display import Image import numpy as np import seaborn as sns sns.set(color codes = True) sns.set(rc={'figure.figsize':(5,5)}) In [26]: # Distribusi dari nilai log 'SALE PRICE' print(df_n['LOG_PRICE'].skew()) sns.distplot(df_n['LOG_PRICE'], bins=100) -0.26418219250538066 <AxesSubplot:xlabel='LOG PRICE', ylabel='Density'> Out[26]: 0.7 0.6 0.5 0.4 0.3 0.2 0.1 0.0 10 LOG_PRICE In [27]: df n['LOG PRICE'].mean() 13.323709361183091 Out[27]: Distribusi dari 'LOG_PRICE' adalah distribui normal karena memiliki kurva kerapatan berbentuk lonceng, simetris, berpusat di sekitar meannya, dengan penyebarannya ditentukan oleh deviasi standarnya yang menunjukkan bahwa data di dekat mean lebih sering terjadi daripada data yang jauh dari mean. In [28]: df n['BUILDING CLASS CATEGORY'].value_counts() 01 ONE FAMILY DWELLINGS 12543 Out[28]: 02 TWO FAMILY DWELLINGS 9736 10 COOPS - ELEVATOR APARTMENTS 2834 13 CONDOS - ELEVATOR APARTMENTS 2689 03 THREE FAMILY DWELLINGS 2293 07 RENTALS - WALKUP APARTMENTS 1608 15 CONDOS - 2-10 UNIT RESIDENTIAL 778 09 COOPS - WALKUP APARTMENTS 547 04 TAX CLASS 1 CONDOS 543 22 STORE BUILDINGS 429 370 12 CONDOS - WALKUP APARTMENTS 14 RENTALS - 4-10 UNIT 311 05 TAX CLASS 1 VACANT LAND 225 219 29 COMMERCIAL GARAGES 44 CONDO PARKING 160 21 OFFICE BUILDINGS 148 143 30 WAREHOUSES 27 FACTORIES 94 77 31 COMMERCIAL VACANT LAND 37 RELIGIOUS FACILITIES 58 58 08 RENTALS - ELEVATOR APARTMENTS 41 TAX CLASS 4 - OTHER 36 43 CONDO OFFICE BUILDINGS 32 06 TAX CLASS 1 - OTHER 32 26 OTHER HOTELS 31 17 CONDO COOPS 31 33 EDUCATIONAL FACILITIES 21 32 HOSPITAL AND HEALTH FACILITIES 19 46 CONDO STORE BUILDINGS 17 16 CONDOS - 2-10 UNIT WITH COMMERCIAL UNIT 15 35 INDOOR PUBLIC AND CULTURAL FACILITIES 14 23 LOFT BUILDINGS 11 47 CONDO NON-BUSINESS STORAGE 11 38 ASYLUMS AND HOMES 11 10 48 CONDO TERRACES/GARDENS/CABANAS 11A CONDO-RENTALS 9 49 CONDO WAREHOUSES/FACTORY/INDUS 7 42 CONDO CULTURAL/MEDICAL/EDUCATIONAL/ETC 2 28 COMMERCIAL CONDOS 36 OUTDOOR RECREATIONAL FACILITIES 34 THEATRES 11 SPECIAL CONDO BILLING LOTS 45 CONDO HOTELS 39 TRANSPORTATION FACILITIES 1 40 SELECTED GOVERNMENTAL FACILITIES 0 25 LUXURY HOTELS 0 18 TAX CLASS 3 - UNTILITY PROPERTIES 0 Name: BUILDING CLASS CATEGORY, dtype: int64 In [29]: sum(df_n['BUILDING CLASS CATEGORY'].value_counts()) Out[29]: In [30]: # Menghitung Distribusi Peluang HOSPITAL AND HEALTH FACILITIES dari BUILDING CLASS CATEGORY P h = 19/36181print('DIstribusi Peluang HOSPITAL AND HEALTH FACILITIES dari BUILDING CLASS CATEGORY adalah :', P_h) DIstribusi Peluang HOSPITAL AND HEALTH FACILITIES dari BUILDING CLASS CATEGORY adalah: 0.0005251375031093668 **Confidence Interval** In [31]: # Menghitung CI HOSPITAL AND HEALTH FACILITIES dari Building Class Category In [32]: # Populasi Building Class Category n = 36181# Proporsi HOSPITAL AND HEALTH FACILITIES dari Building Class Category P h = 19/36181P_h 0.0005251375031093668 Out[32]: In [33]: # Standard Error $se_h = np.sqrt(P_h * (1-P_h)/n)$ se_h 0.00012044316858547533 Out[33]: In [34]: # Menghitung CI menggunakan rumus diatas dengan z-score adalah 1.96 untuk confidence interval 95% z score = 1.96 lcb = P_h - z_score*se_h #lower limit dari CI ucb = P_h + z_score*se_h #Upper limit dari CI lcb, ucb (0.0002890688926818352, 0.0007612061135368985) Out[34]: In [35]: # Cara lain sm.stats.proportion_confint(n*P_h, n) (0.0002890732304979491, 0.0007612017757207846) Out[35]: Jadi, Convidence Interval HOSPITAL AND HEALTH FACILITIES dari Building Class Category adalah (0.0002890732304979491, 0.0007612017757207846) **Hypothesis Testing** In [36]: # Memperbaiki Kolom 'BOROUGH df n['BOROUGH'] = df n['BOROUGH'].astype(str) df_n['BOROUGH'] = df_n['BOROUGH'].str.replace('1','Manhattan') df_n['BOROUGH'] = df_n['BOROUGH'].str.replace('2','Bronx') df_n['BOROUGH'] = df_n['BOROUGH'].str.replace('3','Brooklyn') df_n['BOROUGH'] = df_n['BOROUGH'].str.replace('4','Queens') df_n['BOROUGH'] = df_n['BOROUGH'].str.replace('5','Staten Island') In [37]: df n Out[37]: **TAX BUILDING BUILDING LAND GROSS** RESIDENTIAL COMMERCIAL TOTAL **CLASS** BOROUGH NEIGHBORHOOD **CLASS** BLOCK LOT CLASS AT **SQUARE SQUARE UNITS UNITS UNITS** AT **CATEGORY PRESENT FEET** FEET **PRESENT** 07 RENTALS -1633.0 Manhattan ALPHABET CITY WALKUP 2A 392 6 C2 0 5 6440.0 **APARTMENTS** 07 RENTALS -6794.0 Manhattan ALPHABET CITY WALKUP 2B 402 21 C4 10 0 10 2272.0 **APARTMENTS** 07 RENTALS -**ALPHABET CITY** WALKUP 0 2369.0 Manhattan 2A 404 55 C2 6 6 4615.0 **APARTMENTS** 07 RENTALS -**ALPHABET CITY** Manhattan WALKUP 2B 406 32 C4 8 0 8 1750.0 4226.0 **APARTMENTS** 14 RENTALS -1520.0 Manhattan ALPHABET CITY 2A 391 19 S3 3 1 4 3360.0 4-10 UNIT 02 TWO Staten 2 84541 WOODROW **FAMILY** 7317 126 В2 0 11088.0 2160.0 Island **DWELLINGS** 02 TWO Staten 2400.0 84543 WOODROW **FAMILY** 7349 34 В9 2 0 2 2575.0 Island **DWELLINGS** 02 TWO Staten 2 0 2 2498.0 84544 WOODROW **FAMILY** 7349 78 В9 2377.0 Island **DWELLINGS** 02 TWO Staten 84545 4000.0 WOODROW **FAMILY** 7351 60 В2 2 0 2 1496.0 Island **DWELLINGS** 35 INDOOR Staten **PUBLIC AND** 0 84547 WOODROW 7105 679 P9 10796.0 2400.0 Island **CULTURAL FACILITIES** 36181 rows × 18 columns In [38]: df bor = df n.groupby('BOROUGH', axis=0).sum() df bor Out[38]: LAND **GROSS** RESIDENTIAL COMMERCIAL YEAR **TOTAL SALE PRICE BLOCK** LOT **SQUARE SQUARE** LOG_PRICE **BUILT** UNITS **UNITS** UNITS FEET FEET **BOROUGH Bronx** 20929685 1487147 10683 13502440.0 12851539.0 8833109 2.923204e+09 11212 63169.173827 **Brooklyn** 63463621 5690738 23744 1428 25375 23991850.0 24391594.0 26728528 1.562624e+10 203589.977077 876068 32354 Manhattan 7358 543 7894 2204614.0 10866383.0 1160509 2.638975e+09 9004.625369 **Queens** 85826759 579994 20866 3417 24275 40616295.0 26792130.0 20701090 8.010454e+09 142267.883682 Staten 11450310.0 16527557 402935 6651 478 7123 28930572.0 9640993 2.628729e+09 64033.468442 Island Berdasarkan dataset diatas, apakah total unit rata-rata per penjualan pada borough Brooklyn lebih besar secara signifikan daripada Queens • H0: tidak ada perbedaan secara signifikan pada total unit rata-rata per penjualan antara borough Brooklyn dan Queens H1: Terdapat perbedaan secara signifikan pada total unit rata-rata per penjualan antara borough Brooklyn dan Queens In [39]: Brooklyn = df_n[df n['BOROUGH'] == 'Brooklyn'] Queens = df_n[df_n['BOROUGH']=='Queens'] In [40]: total_unit_Q = df_bor.iloc[-2, 4] mu_Q = Queens['TOTAL UNITS'].mean() std_Q = Queens['TOTAL UNITS'].std() total_unit_Q, mu_Q, std_Q (24275, 2.273152916939788, 29.12838869550192) Out[40]: In [41]: total_unit_B = df_bor.iloc[-4, 4] mu B = Brooklyn['TOTAL UNITS'].mean() std_B = Brooklyn['TOTAL UNITS'].std() total_unit_B, mu_B, std_B (25375, 1.6833620804033436, 4.370729519754011) Out[41]: In [45]: from statsmodels.stats.weightstats import ztest ztest, pval= ztest(Brooklyn['TOTAL UNITS'], Queens['TOTAL UNITS']) print("pval: ",float(pval)) **if** pval<0.05: print("Karena p-value lebih rendah dari significance level yang kita tentukan yaitu 0.05. Jadi, kita Tolak print ("Karena p-value lebih besar sama dengan significance level yang kita tentukan yaitu 0.05. Jadi, kita pval: 0.014389036830450569 Karena p-value lebih rendah dari significance level yang kita tentukan yaitu 0.05. Jadi, kita Tolak H0 Di sini p-value lebih rendah dari significance level yang kita tentukan yaitu 0.05. Jadi, kita reject the null hypothesis. Artinya, terdapat perbedaan yang signifikan pada total unit rata-rata per penjualan antara borough Brooklyn dan Queens