Impact of computing on conventional businesses and markets

The porpuse of this reseach is evaluate how advances in computing in the last decade has impacted on existent conventional businesses and markets, As rule we will analyze industries that existed long behore computing.

Dependencies

In [ ]:
```
# Standard packages
import pandas as pd
import numpy as np
import re

# Installed packages
from IPython.display import display
from matplotlib import pyplot as plt
%pip install seaborn
import seaborn as sns
from scipy import stats
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import train_test_split

# Local packages
# NOTE: avoid having to use a local module to ease use of Google Colab
```

```
Defaulting to user installation because normal site-packages is not writ
eable
Requirement already satisfied: seaborn in /home/angrygingy/.local/lib/py
thon3.10/site-packages (0.12.2)
Requirement already satisfied: numpy!=1.24.0,>=1.17 in /home/angryging
y/.local/lib/python3.10/site-packages (from seaborn) (1.23.5)
Requirement already satisfied: pandas>=0.25 in /home/angrygingy/.local/l
ib/python3.10/site-packages (from seaborn) (1.5.3)
Requirement already satisfied: matplotlib!=3.6.1,>=3.1 in /home/angrygin
gy/.local/lib/python3.10/site-packages (from seaborn) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /home/angrygingy/.loc
al/lib/python3.10/site-packages (from matplotlib!=3.6.1,>=3.1->seaborn)
(1.0.7)
Requirement already satisfied: cycler>=0.10 in /home/angrygingy/.local/l
ib/python3.10/site-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (0.1
1.0)
Requirement already satisfied: fonttools>=4.22.0 in /home/angrygingy/.lo
cal/lib/python3.10/site-packages (from matplotlib!=3.6.1,>=3.1->seaborn)
(4.39.3)
Requirement already satisfied: kiwisolver>=1.0.1 in /home/angrygingy/.lo
cal/lib/python3.10/site-packages (from matplotlib!=3.6.1,>=3.1->seaborn)
(1.4.4)
Requirement already satisfied: packaging>=20.0 in /home/angrygingy/.loca
l/lib/python3.10/site-packages (from matplotlib!=3.6.1,>=3.1->seaborn)
(23.0)
Requirement already satisfied: pillow>=6.2.0 in /usr/lib/python3/dist-pa
ckages (from matplotlib!=3.6.1,>=3.1->seaborn) (9.0.1)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/lib/python3/dist
-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (2.4.7)
Requirement already satisfied: python-dateutil>=2.7 in /home/angryging
y/.local/lib/python3.10/site-packages (from matplotlib!=3.6.1,>=3.1->sea
born) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/lib/python3/dist-pac
kages (from pandas>=0.25->seaborn) (2022.1)
Requirement already satisfied: six>=1.5 in /home/angrygingy/.local/lib/p
ython3.10/site-packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=
3.1->seaborn) (1.12.0)

[notice] A new release of pip is available: 23.1 -> 23.1.2
[notice] To update, run: pip install --upgrade pip
Note: you may need to restart the kernel to use updated packages.
```

Globals and constants

In [ ]:

```python
# Constants
DATE_COLUMN = 'Year'
MIN_YEAR = 2001
MAX_YEAR = 2020
DATASETS_FOLDER = './content'
SAVE_CLEANED_DATA = False

# Global state
population = None # Used to normalize data
```

Reviewing Computing Advances

Transistor information was extracted from wikipedia transistor count using wikitable2csv.ggor.de to extract the tables.

In [ ]:
```
# We will merge all computer dataframes into one
computer_dfs = []
```

In [ ]:
```
def ensure_date_type(df: pd.DataFrame, date_column:str=DATE_COLUMN) -> pd
    """Ensure date type"""
    df[date_column] = df[date_column].astype(int)
    return df

def keep_columns(df:pd.DataFrame, columns:list) -> pd.DataFrame:
    """Keep only the specified columns"""
    return df[columns]

def date_to_year(df:pd.DataFrame, date_column:str) -> pd.DataFrame:
    """Convert DATE_COLUMN to year and rename column to 'Year'"""
    # Convert to year
    year_pattern = r'\d{4}'
    df[date_column] = df[date_column].astype(str)
    df = df[df[date_column].str.contains(year_pattern)]
    df[date_column] = df[date_column].apply(lambda x: re.findall(year_pat
    # Rename
    if date_column != DATE_COLUMN:
        df = df.rename(columns={date_column: DATE_COLUMN})
    return df

def remove_commas(df:pd.DataFrame) -> pd.DataFrame:
    """Remove commas from all columns"""
    return df.apply(lambda x: x.str.replace(',', ''))

def convert_to_float(df:pd.DataFrame, columns:list) -> pd.DataFrame:
    """Convert the specified columns to float"""
    for col in columns:
        df[col] = pd.to_numeric(df[col], errors='coerce')
    return df

def cut_add_years(
        df: pd.DataFrame,
        year_column:str=DATE_COLUMN,
        min_year:int=MIN_YEAR,
        max_year:int=MAX_YEAR
        ) -> pd.DataFrame:
    """Cut the dataframe to the specified years and add missing years"""
    df = ensure_date_type(df, year_column)
    # Add missing years
    for year in range(min_year, max_year):
        if year not in df[year_column].values:
            df = pd.concat([df, pd.DataFrame.from_records([{ year_column:
    df = df.sort_values(by=[year_column]).reset_index(drop=True)
    # Cut
    df = df[(df[year_column] >= min_year) & (df[year_column] <= max_year)
    return df

def keep_highest_per_year(
        df: pd.DataFrame,
        value_column:str,
        year_column:str=DATE_COLUMN
        ) -> pd.DataFrame:
    """Keep only the highest value for each year, useful when we want onl
       advance of a technology, so we don't care about the lower values""
```

```
    df = df.sort_values(by=[year_column, value_column], ascending=False)
    df = df.drop_duplicates(subset=[year_column], keep='first')
    # Back to the original order
    df = df.sort_values(by=[year_column]).reset_index(drop=True)
    return df

def year_column_to_row(df:pd.DataFrame, country_row:str, new_column_name:
    """Converts columns to rows and filters by country, useful for the wo
    # Filter rows by country
    df = df[df['Country Name'] == country_row]
    # Remove columns that are not a year
    df = df[df.columns[df.columns.str.contains(r'\d{4}')]]
    # Convert columns to rows
    df = df.melt(id_vars=[], var_name=DATE_COLUMN, value_name=new_column_
    return df

def normalize_with_population(df:pd.DataFrame, column:str) -> pd.DataFram
    """Normalize the value column with the population column"""
    return df ## TODO: fix this
    assert population is not None, 'Population dataframe is not loaded'
    df[column] = np.divide(df[column], population['US Population']) * 100
    return df

def merge_by_year(dataframes:list) -> pd.DataFrame:
    """Merge all dataframes by year,
       NOTE: all dataframes should have the same year column values"""
    result = pd.DataFrame()
    result[DATE_COLUMN] = dataframes[0][DATE_COLUMN].unique()
    result = ensure_date_type(result)
    # Merge dataframes
    for df in dataframes:
        df = ensure_date_type(df)
        result = pd.merge(result, df, on=DATE_COLUMN, how='outer')
    result = cut_add_years(result)
    return result
```

Flash memory

In [ ]:

```
flash = pd.read_csv(f'{DATASETS_FOLDER}/flash.csv')
#
print('# Original data')
display(flash.tail())
#
flash = keep_columns(flash, ['FGMOS transistor count', 'Date of introduct
flash = date_to_year(flash, 'Date of introduction')
flash = remove_commas(flash)
flash = convert_to_float(flash, ['FGMOS transistor count'])
flash = cut_add_years(flash)
flash = keep_highest_per_year(flash, 'FGMOS transistor count')
flash = flash.fillna(method='ffill')
computer_dfs.append(flash)
#
print('# Cleaned data')
display(flash.tail())
display(flash.describe())
flash.plot(x=DATE_COLUMN, y='FGMOS transistor count', title='FGMOS transi
plt.show()
```

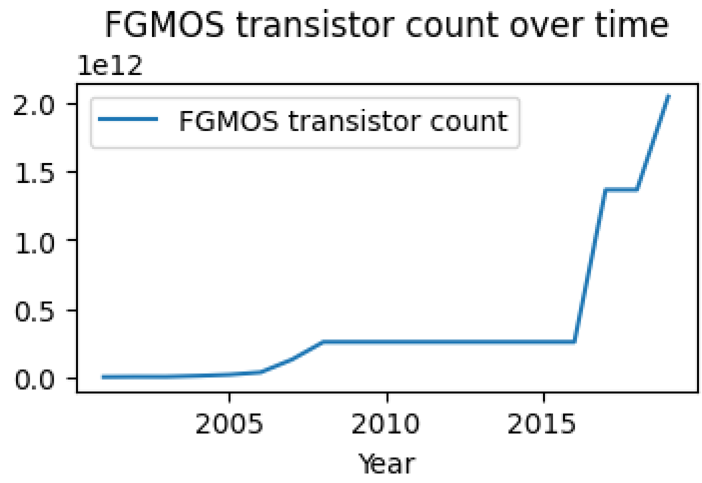
```
# Original data
```

	Chip name	Capacity (bits)	Flash type	FGMOS transistor count	Date of introduction	Manufacturer(s)	Proce
19	KLMCG8GE4A	512 Gb	Stacked 2-bit NAND	256,000,000,000	2011	Samsung	
20	KLUFG8R1EM	4 Tb	Stacked 3-bit V-NAND	1,365,333,333,504	2017	Samsung	
21	eUFS (1 TB)	8 Tb	Stacked 4-bit V-NAND	2,048,000,000,000	2019	Samsung	
22	?	1 Tb	232L TLC NAND die	333,333,333,333	2022	Micron	
23	?	16 Tb	232L package	5,333,333,333,333	2022	Micron	

```
# Cleaned data
```

	FGMOS transistor count	Year
14	2.560000e+11	2015
15	2.560000e+11	2016
16	1.365333e+12	2017
17	1.365333e+12	2018
18	2.048000e+12	2019

	FGMOS transistor count	Year
count	1.900000e+01	19.000000
mean	3.829278e+11	2010.000000
std	5.649140e+11	5.627314
min	5.368709e+08	2001.000000
25%	2.576980e+10	2005.500000
50%	2.560000e+11	2010.000000
75%	2.560000e+11	2014.500000
max	2.048000e+12	2019.000000



FPGA

In [ ]:
```
fpga = pd.read_csv(f'{DATASETS_FOLDER}/fpga.csv')
#
print('# Original data')
display(fpga.tail())
#
fpga = keep_columns(fpga, ['Transistor count', 'Date of introduction'])
fpga = date_to_year(fpga, 'Date of introduction')
fpga = remove_commas(fpga)
fpga = convert_to_float(fpga, ['Transistor count'])
fpga = cut_add_years(fpga)
fpga = fpga.rename(columns={'Transistor count': 'FPGA transistor count'})
fpga = keep_highest_per_year(fpga, 'FPGA transistor count')
fpga = fpga.fillna(method='ffill')
computer_dfs.append(fpga)
#
print('# Cleaned data')
display(fpga.tail())
display(fpga.describe())
fpga.plot(x=DATE_COLUMN, y='FPGA transistor count', title='FPGA transisto
plt.show()
```

```
# Original data
```

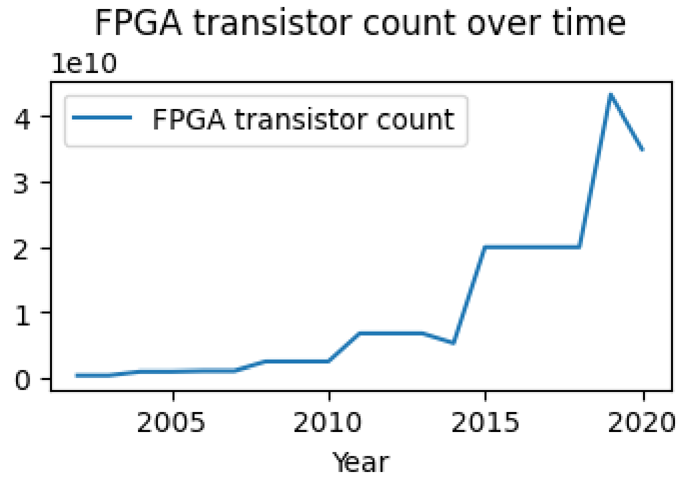
	FPGA	Transistor count	Date of introduction	Designer	Manufacturer	Process	Area	Tr
11	Virtex-Ultrascale VU440	20,000,000,000	Q1 2015	Xilinx	TSMC	20 nm	NaN	
12	Virtex-Ultrascale+ VU19P	35,000,000,000	2020	Xilinx	TSMC	16 nm	900 mm2	38
13	Versal VC1902	37,000,000,000	2H 2019	Xilinx	TSMC	7 nm	NaN	
14	Stratix 10 GX 10M	43,300,000,000	Q4 2019	Intel	Intel	14 nm	1,400 mm2	30
15	Versal VP1802	92,000,000,000	2021 ?	Xilinx	TSMC	7 nm	NaN	

```
# Cleaned data
```

```
/tmp/ipykernel_6563/3484873384.py:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-d
ocs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[date_column] = df[date_column].apply(lambda x: re.findall(year_patt
ern, x)[0])
```

	FPGA transistor count	Year
15	2.000000e+10	2016
16	2.000000e+10	2017
17	2.000000e+10	2018
18	4.330000e+10	2019
19	3.500000e+10	2020

	FPGA transistor count	Year
count	1.900000e+01	20.00000
mean	1.034526e+10	2010.50000
std	1.259800e+10	5.91608
min	4.300000e+08	2001.00000
25%	1.100000e+09	2005.75000
50%	5.300000e+09	2010.50000
75%	2.000000e+10	2015.25000
max	4.330000e+10	2020.00000



GPU

In [ ]:
```
gpus = pd.read_csv(f'{DATASETS_FOLDER}/gpus.csv')
#
print('# Original data')
display(gpus.tail())
#
gpus = keep_columns(gpus, ['Transistor count', 'Year'])
gpus = date_to_year(gpus, 'Year')
gpus = remove_commas(gpus)
gpus = convert_to_float(gpus, ['Transistor count'])
```

```
gpus = cut_add_years(gpus)
gpus = gpus.rename(columns={'Transistor count': 'GPU transistor count'})
gpus = keep_highest_per_year(gpus, 'GPU transistor count')
gpus = gpus.fillna(method='ffill')
computer_dfs.append(gpus)
#
print('# Cleaned data')
display(gpus.tail())
display(gpus.describe())
gpus.plot(x='Year', y='GPU transistor count', title='GPU transistor count
plt.show()
```

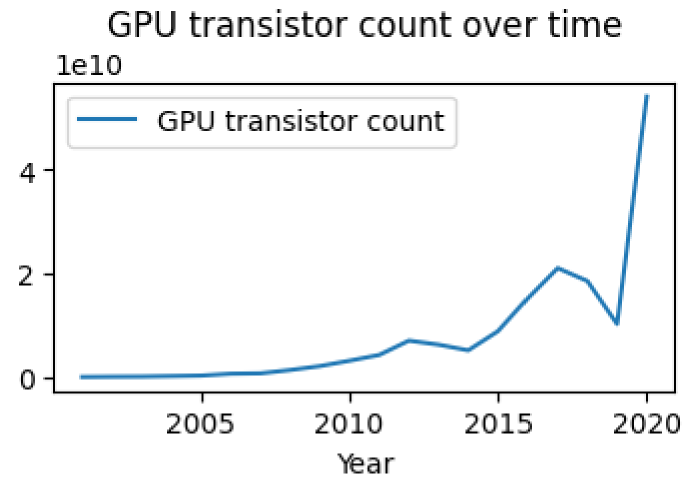
```
# Original data
```

	Processor	Transistor count	Year	Designer(s)	Fab(s)	Process	Area	Tra
158	AD102 Ada Lovelace	76,300,000,000	2022	Nvidia	TSMC	4 nm	608.4 mm²	
159	AD103 Ada Lovelace	45,900,000,000	2022	Nvidia	TSMC	4 nm	378.6 mm²	
160	AD104 Ada Lovelace	35,800,000,000	2022	Nvidia	TSMC	4 nm	294.5 mm²	
161	Navi 31 RDNA3	58,000,000,000	2022	AMD	TSMC	5 nm (GCD) 6 nm (MCD)	531 mm² (MCM) 306 mm² (GCD) 6×37.5 mm² (MCD)	10 13
162	Navi 33 RDNA3	13,300,000,000	2023	AMD	TSMC	6 nm	204 mm²	

```
# Cleaned data
```

	GPU transistor count	Year
15	1.530000e+10	2016
16	2.110000e+10	2017
17	1.860000e+10	2018
18	1.030000e+10	2019
19	5.420000e+10	2020

	GPU transistor count	Year
count	2.000000e+01	20.00000
mean	8.016336e+09	2010.50000
std	1.260009e+10	5.91608
min	6.000000e+07	2001.00000
25%	5.910000e+08	2005.75000
50%	3.756356e+09	2010.50000
75%	9.250000e+09	2015.25000
max	5.420000e+10	2020.00000



Microprocessor

In [ ]:
```
microprocessors = pd.read_csv(f'{DATASETS_FOLDER}/microprocessors.csv')
#
print('# Original data')
display(microprocessors.tail())
#
microprocessors = keep_columns(microprocessors, ['Transistor count', 'Yea
microprocessors = date_to_year(microprocessors, 'Year')
microprocessors = remove_commas(microprocessors)
microprocessors = microprocessors[microprocessors['Transistor count'].str
microprocessors = convert_to_float(microprocessors, ['Transistor count'])
microprocessors = microprocessors.rename(columns={'Transistor count': 'Mi
microprocessors = cut_add_years(microprocessors)
microprocessors = keep_highest_per_year(microprocessors, 'Microprocessor
microprocessors = microprocessors.fillna(method='ffill')
computer_dfs.append(microprocessors)
#
print('# Cleaned data')
display(microprocessors.tail())
display(microprocessors.describe())
microprocessors.plot(x='Year', y='Microprocessor transistor count', title
plt.show()
```

```
# Original data
```

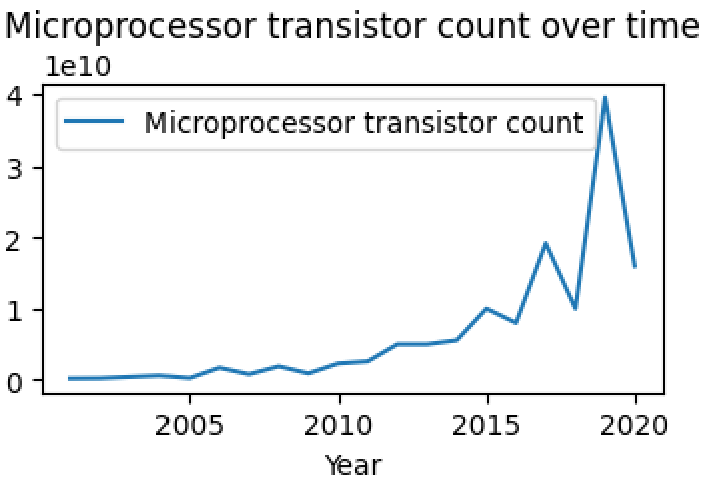
	Processor	Transistor count	Year	Designer	Process\n(nm)	Area (mm2)	.
229	AMD EPYC Genoa (4th gen/9004 series) 13-chip m...	90,000,000,000	2022	AMD	5 nm (CCD)\n6 nm (IOD)	1,263.34 mm²\n12×72.225 (CCD)\n396.64 (IOD)	7
230	Sapphire Rapids quad-chip module (up to 60 cor...	44,000,000,000–48,000,000,000	2023	Intel	Intel 7 (10 nm ESF)	1,600 mm2	27 \n3
231	Apple M2 Pro (12-core 64-bit ARM64 SoC, SIMD, ...	40,000,000,000	2023	Apple	5 nm	?	
232	Apple M2 Max (12-core 64-bit ARM64 SoC, SIMD, ...	67,000,000,000	2023	Apple	5 nm	?	
233	Processor	Transistor count	Year	Designer	Process\n(nm)	Area (mm2)	

```
# Cleaned data
```

```
/tmp/ipykernel_6563/3484873384.py:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-d
ocs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[date_column] = df[date_column].apply(lambda x: re.findall(year_patt
ern, x)[0])
```

	Microprocessor transistor count	Year
15	8000000000	2016
16	19200000000	2017
17	10000000000	2018
18	39540000000	2019
19	16000000000	2020

	Microprocessor transistor count	Year
count	2.000000e+01	20.00000
mean	6.507800e+09	2010.50000
std	9.477374e+09	5.91608
min	1.910000e+08	2001.00000
25%	7.397500e+08	2005.75000
50%	2.450000e+09	2010.50000
75%	8.500000e+09	2015.25000
max	3.954000e+10	2020.00000



RAM

Note that we will drop this dataset because contains a lot of NaN values

In [ ]:
```
ram = pd.read_csv(f'{DATASETS_FOLDER}/ram.csv')
#
print('# Original data')
display(ram.tail())
#
ram = keep_columns(ram, ['Date of introduction', 'Transistor count'])
ram = date_to_year(ram, 'Date of introduction')
ram = remove_commas(ram)
ram = convert_to_float(ram, ['Transistor count'])
ram = ram.rename(columns={'Transistor count': 'RAM transistor count'})
ram = cut_add_years(ram)
ram = keep_highest_per_year(ram, 'RAM transistor count')
ram = ram.fillna(method='ffill')
# BAD: computer_dfs.append(ram) this dataset has a lot of Nan values
# show
print('# Cleaned data')
display(ram.tail())
display(ram.describe())
ram.plot(x='Year', y='RAM transistor count', title='RAM transistor count
plt.show()
```

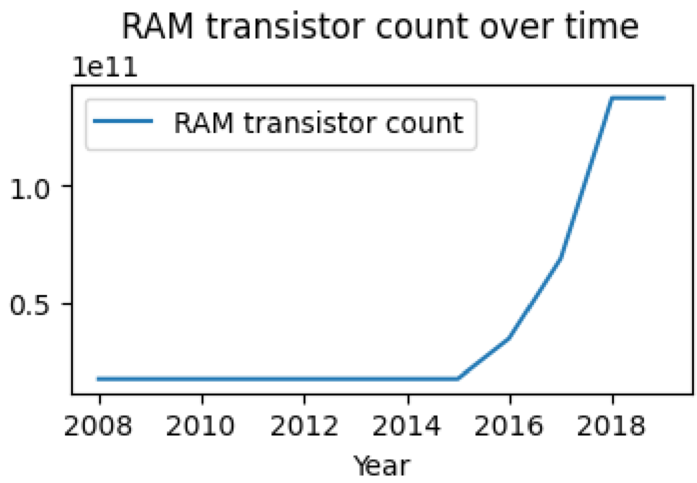
```
# Original data
```

	Chip name	Capacity (bits)	RAM type	Transistor count	Date of introduction	Manufacturer(s)	Process	Area
43	?	16 Gb	SDRAM (DDR3)	17,179,869,184	2008	Samsung	50 nm	?
44	?	32 Gb	SDRAM (HBM2)	34,359,738,368	2016	Samsung	20 nm	?
45	?	64 Gb	SDRAM (HBM2)	68,719,476,736	2017	Samsung	20 nm	?
46	?	128 Gb	SDRAM (DDR4)	137,438,953,472	2018	Samsung	10 nm	?
47	?	?	RRAM (3DSoC)	?	2019	SkyWater Technology	90 nm	?

```
# Cleaned data
```

	Year	RAM transistor count
14	2015	1.717987e+10
15	2016	3.435974e+10
16	2017	6.871948e+10
17	2018	1.374390e+11
18	2019	1.374390e+11

	Year	RAM transistor count
count	19.000000	1.200000e+01
mean	2010.000000	4.294967e+10
std	5.627314	4.661933e+10
min	2001.000000	1.717987e+10
25%	2005.500000	1.717987e+10
50%	2010.000000	1.717987e+10
75%	2014.500000	4.294967e+10
max	2019.000000	1.374390e+11



ROM

Note that we will drop this data since this lack of data from 2000s up to now

In [ ]:
```
rom = pd.read_csv(f'{DATASETS_FOLDER}/rom.csv')
#
print('# Original data')
display(rom.tail())
#
rom = keep_columns(rom, ['Date of introduction', 'Transistor count'])
rom = date_to_year(rom, 'Date of introduction')
rom = remove_commas(rom)
rom = convert_to_float(rom, ['Transistor count'])
rom = rom.rename(columns={'Transistor count': 'ROM transistor count'})
rom = cut_add_years(rom)
rom = keep_highest_per_year(rom, 'ROM transistor count')
rom = rom.fillna(method='ffill')
# BAD: computer_dfs.append(rom) this lacks data from 2000 up to now
# show
print('# Cleaned data')
display(rom.tail())
display(rom.describe())
rom.plot(x='Year', y='ROM transistor count', title='ROM transistor count
plt.show()
```

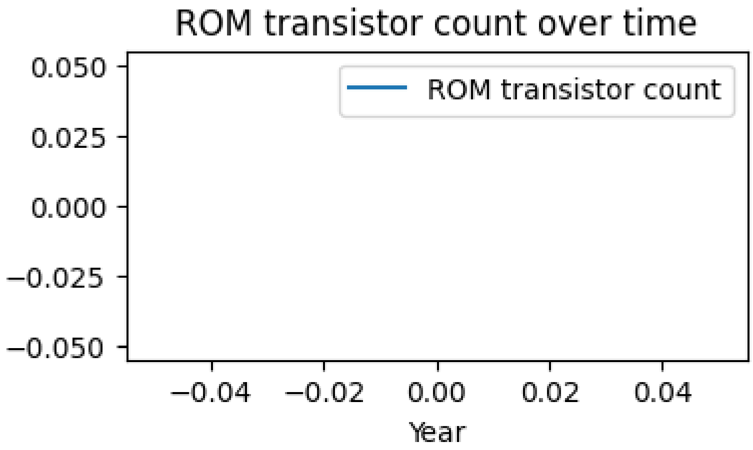
```
# Original data
```

	Chip name	Capacity (bits)	ROM type	Transistor count	Date of introduction	Manufacturer(s)	Process	Area	Ref
17	27512	512 Kb	EPROM (HMOS)	524,288	1984	Intel	?	?	NaN
18	?	1 Mb	EPROM (CMOS)	1,048,576	1984	NEC	1,200 nm	?	NaN
19	?	4 Mb	EPROM (CMOS)	4,194,304	1987	Toshiba	800 nm	?	NaN
20	?	16 Mb	EPROM (CMOS)	16,777,216	1990	NEC	600 nm	?	NaN
21	?	16 Mb	MROM	16,777,216	1995	AKM, Hitachi	?	?	NaN

```
# Cleaned data
```

	Year	ROM transistor count
14	2015	NaN
15	2016	NaN
16	2017	NaN
17	2018	NaN
18	2019	NaN

	Year	ROM transistor count
count	19.000000	0.0
mean	2010.000000	NaN
std	5.627314	NaN
min	2001.000000	NaN
25%	2005.500000	NaN
50%	2010.000000	NaN
75%	2014.500000	NaN
max	2019.000000	NaN



Internet

In [ ]:
```
internet = pd.read_csv(f'{DATASETS_FOLDER}/theworldbank_internet.csv')
#
print('# Original data')
display(internet.tail())
#
internet = year_column_to_row(internet, 'United States', 'US internet per
internet = cut_add_years(internet)
computer_dfs.append(internet)
#
print('# Cleaned data')
display(internet.tail())
display(internet.describe())
internet.plot(x='Year', y='US internet percentage', title='US internet pe
plt.show()
```

```
# Original data
```

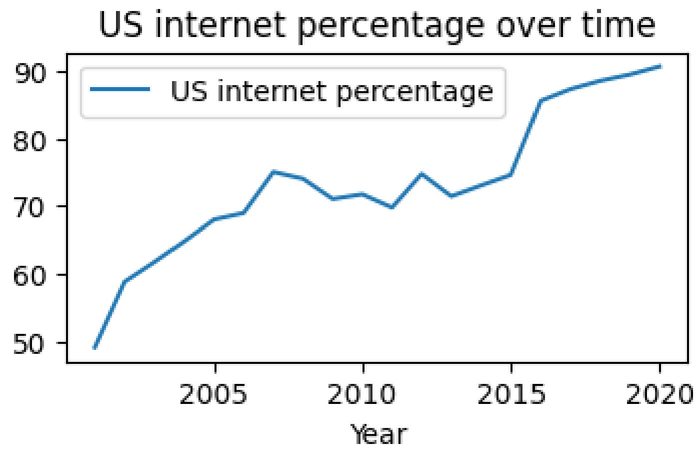
	Country Name	Country Code	Indicator Name	Indicator Code	1960	1961	1962	1963	1964	1965	..
261	Kosovo	XKX	Individuals using the Internet (% of population)	IT.NET.USER.ZS	NaN	NaN	NaN	NaN	NaN	NaN	..
262	Yemen, Rep.	YEM	Individuals using the Internet (% of population)	IT.NET.USER.ZS	NaN	NaN	NaN	NaN	NaN	NaN	..
263	South Africa	ZAF	Individuals using the Internet (% of population)	IT.NET.USER.ZS	NaN	NaN	NaN	NaN	NaN	NaN	..
264	Zambia	ZMB	Individuals using the Internet (% of population)	IT.NET.USER.ZS	NaN	NaN	NaN	NaN	NaN	NaN	..
265	Zimbabwe	ZWE	Individuals using the Internet (% of population)	IT.NET.USER.ZS	NaN	NaN	NaN	NaN	NaN	NaN	..

5 rows × 68 columns

```
# Cleaned data
```

	Year	US internet percentage
56	2016	85.544421
57	2017	87.274889
58	2018	88.498903
59	2019	89.430285
60	2020	90.620470

	Year	US internet percentage
count	20.00000	20.000000
mean	2010.50000	73.383174
std	5.91608	10.809027
min	2001.00000	49.080832
25%	2005.75000	68.690408
50%	2010.50000	72.345000
75%	2015.25000	77.636105
max	2020.00000	90.620470



In [ ]:
```
## TODO: add phones related data
```

In [ ]:
```
## TODO: add AI related data
```

In [ ]:
```
## TODO: add SSD related data
```

Merge all computing advances into a single dataframe

In [ ]:
```
computer_advances = merge_by_year(computer_dfs)
# Review if computer advances final dataframe were correctly merged
computer_advances.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20 entries, 0 to 19
Data columns (total 6 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Year                            20 non-null     int64
 1   FGMOS transistor count          19 non-null     float64
 2   FPGA transistor count           19 non-null     float64
 3   GPU transistor count            20 non-null     float64
 4   Microprocessor transistor count 20 non-null     int64
 5   US internet percentage          20 non-null     float64
dtypes: float64(4), int64(2)
memory usage: 1.1 KB
```

Reviewing the United States economy

Population, GDP and internet datasets were obtained from worldbank.org.

Population

In [ ]:
```
population = pd.read_csv(f'{DATASETS_FOLDER}/theworldbank_population.csv'
#
print('# Original data')
display(population.tail())
#
population = year_column_to_row(population, 'United States', 'US Populati
population = cut_add_years(population)
#
print('# Cleaned data')
display(population.tail())
```

```
display(population.describe())
population.plot(x='Year', y='US Population', title='US Population over ti
plt.show()
```

```
# Original data
```

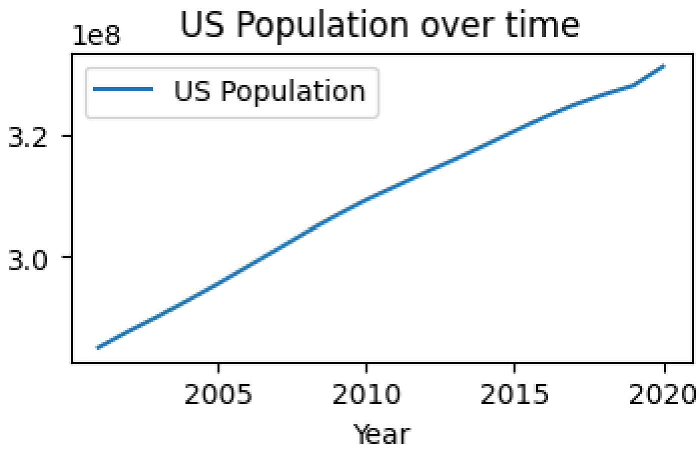
	Country Name	Country Code	Indicator Name	Indicator Code	1960	1961	1962	
261	Kosovo	XKX	Population, total	SP.POP.TOTL	947000.0	966000.0	994000.0	102
262	Yemen, Rep.	YEM	Population, total	SP.POP.TOTL	5542459.0	5646668.0	5753386.0	586
263	South Africa	ZAF	Population, total	SP.POP.TOTL	16520441.0	16989464.0	17503133.0	1804
264	Zambia	ZMB	Population, total	SP.POP.TOTL	3119430.0	3219451.0	3323427.0	343
265	Zimbabwe	ZWE	Population, total	SP.POP.TOTL	3806310.0	3925952.0	4049778.0	417

5 rows × 67 columns

```
# Cleaned data
```

	Year	US Population
56	2016	323071755.0
57	2017	325122128.0
58	2018	326838199.0
59	2019	328329953.0
60	2020	331501080.0

	Year	US Population
count	20.00000	2.000000e+01
mean	2010.50000	3.093169e+08
std	5.91608	1.450577e+07
min	2001.00000	2.849690e+08
25%	2005.75000	2.976641e+08
50%	2010.50000	3.104553e+08
75%	2015.25000	3.213222e+08
max	2020.00000	3.315011e+08



GDP

In [ ]:
```
gdp = pd.read_csv(f'{DATASETS_FOLDER}/theworldbank_gdp.csv')
#
print('# Original data')
display(gdp.tail())
#
gdp = year_column_to_row(gdp, 'United States', 'US GDP')
gdp = cut_add_years(gdp)
gdp = normalize_with_population(gdp, 'US GDP')
#
print('# Cleaned data')
display(gdp.tail())
display(gdp.describe())
gdp.plot(x='Year', y='US GDP', title='US GDP per 100k people over time',
plt.show()
```

```
# Original data
```

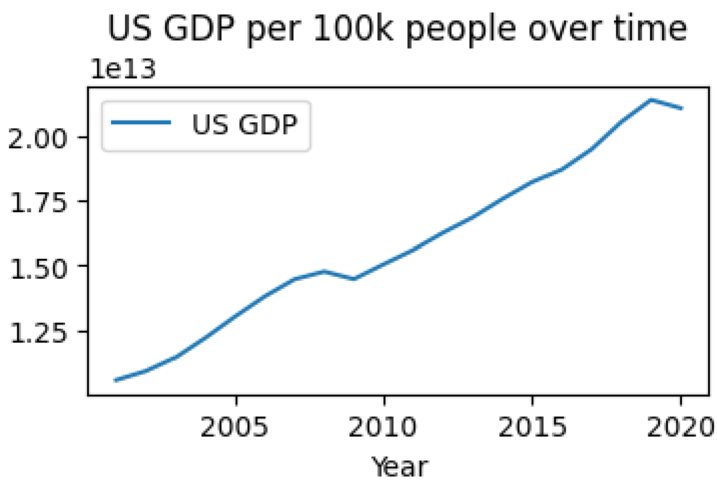
	Country Name	Country Code	Indicator Name	Indicator Code	1960	1961	19
261	Kosovo	XKX	GDP (current US$)	NY.GDP.MKTP.CD	NaN	NaN	N
262	Yemen, Rep.	YEM	GDP (current US$)	NY.GDP.MKTP.CD	NaN	NaN	N
263	South Africa	ZAF	GDP (current US$)	NY.GDP.MKTP.CD	8.748597e+09	9.225996e+09	9.813996e+
264	Zambia	ZMB	GDP (current US$)	NY.GDP.MKTP.CD	7.130000e+08	6.962857e+08	6.931429e+
265	Zimbabwe	ZWE	GDP (current US$)	NY.GDP.MKTP.CD	1.052990e+09	1.096647e+09	1.117602e+

5 rows × 67 columns

```
# Cleaned data
```

	Year	US GDP
56	2016	1.869511e+13
57	2017	1.947734e+13
58	2018	2.053306e+13
59	2019	2.138098e+13
60	2020	2.106047e+13

	Year	US GDP
count	20.00000	2.000000e+01
mean	2010.50000	1.582056e+13
std	5.91608	3.345485e+12
min	2001.00000	1.058193e+13
25%	2005.75000	1.362149e+13
50%	2010.50000	1.532435e+13
75%	2015.25000	1.832829e+13
max	2020.00000	2.138098e+13



In [ ]:
```
economy = merge_by_year([gdp, population])
# Review if economy final dataframe were correctly merged
economy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20 entries, 0 to 19
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Year           20 non-null     int64  
 1   US GDP         20 non-null     float64
 2   US Population  20 non-null     float64
dtypes: float64(2), int64(1)
memory usage: 640.0 bytes
```

Reviewing real estate sales

US 2001-2020 real state sales dataset was obtained from data.gov.

In [ ]:
```
real_estate_sales = pd.read_csv(f'{DATASETS_FOLDER}/real_estate_sales.csv
#
print('# Original data')
display(real_estate_sales.tail())
#
real_estate_sales = keep_columns(real_estate_sales, [
    'Date Recorded', 'Sale Amount', 'Property Type', 'Residential Type',
    ])
# Save cleaned data because github doesn't allow files larger than 100MB
if SAVE_CLEANED_DATA:
    real_estate_sales.to_csv(f'{DATASETS_FOLDER}/real_estate_sales.csv',
real_estate_sales = date_to_year(real_estate_sales, 'Date Recorded')
#
print('# Cleaned data')
display(real_estate_sales.tail())
display(real_estate_sales.describe())
```

```
# Original data
/tmp/ipykernel_6563/1021896824.py:1: DtypeWarning: Columns (2,3) have mi
xed types. Specify dtype option on import or set low_memory=False.
  real_estate_sales = pd.read_csv(f'{DATASETS_FOLDER}/real_estate_sales.
csv')
```

	Date Recorded	Sale Amount	Property Type	Residential Type
997208	06/24/2020	53100.0	Single Family	Single Family
997209	11/27/2019	76000.0	Single Family	Single Family
997210	04/27/2020	210000.0	Single Family	Single Family
997211	06/03/2020	280000.0	Single Family	Single Family
997212	12/20/2019	7450000.0	NaN	NaN

```
/tmp/ipykernel_6563/3484873384.py:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-d
ocs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[date_column] = df[date_column].apply(lambda x: re.findall(year_patt
ern, x)[0])
# Cleaned data
```

	Year	Sale Amount	Property Type	Residential Type
997208	2020	53100.0	Single Family	Single Family
997209	2019	76000.0	Single Family	Single Family
997210	2020	210000.0	Single Family	Single Family
997211	2020	280000.0	Single Family	Single Family
997212	2019	7450000.0	NaN	NaN

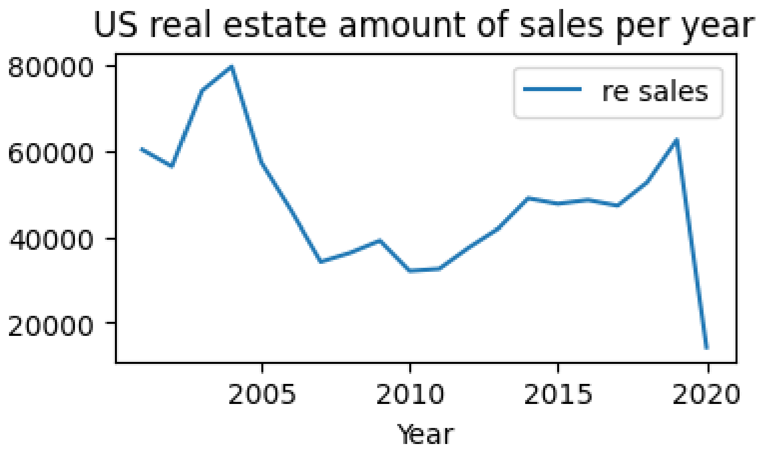
	Sale Amount
count	9.972110e+05
mean	3.911520e+05
std	5.347276e+06
min	0.000000e+00
25%	1.400000e+05
50%	2.250000e+05
75%	3.650000e+05
max	5.000000e+09

Sales per year

In [ ]:
```
# Calculate
re_sales_per_year = pd.DataFrame()
re_sales_per_year['Year'] = real_estate_sales[DATE_COLUMN].unique()
re_sales_per_year = ensure_date_type(re_sales_per_year)
re_sales_per_year['re sales'] = real_estate_sales.groupby(DATE_COLUMN).si
re_sales_per_year = cut_add_years(re_sales_per_year)
re_sales_per_year = re_sales_per_year.fillna(method='ffill')
re_sales_per_year = normalize_with_population(re_sales_per_year, 're sale
# Show
display(re_sales_per_year) # we show all the data because it's not too mu
display(re_sales_per_year.describe())
re_sales_per_year.plot(
    x=DATE_COLUMN,
    y='re sales',
    title='US real estate amount of sales per year',
    figsize=(4, 2)
    )
plt.show()
```

	Year	re sales
1	2001	60207
2	2002	56317
3	2003	73943
4	2004	79566
5	2005	57250
6	2006	46138
7	2007	34195
8	2008	36305
9	2009	39128
10	2010	32088
11	2011	32568
12	2012	37513
13	2013	41941
14	2014	48894
15	2015	47611
16	2016	48493
17	2017	47165
18	2018	52622
19	2019	62534
20	2020	14291

	Year	re sales
count	20.00000	20.000000
mean	2010.50000	47438.450000
std	5.91608	15192.165091
min	2001.00000	14291.000000
25%	2005.75000	37211.000000
50%	2010.50000	47388.000000
75%	2015.25000	56550.250000
max	2020.00000	79566.000000



Invested per year

In [ ]:
```
# Calculate
re_investment_per_year = pd.DataFrame()
re_investment_per_year['Year'] = real_estate_sales[DATE_COLUMN].unique()
re_investment_per_year = ensure_date_type(re_investment_per_year)
re_investment_per_year['re investment'] = real_estate_sales.groupby(DATE_
re_investment_per_year = cut_add_years(re_investment_per_year)
re_investment_per_year = normalize_with_population(re_investment_per_year
# Show
display(re_investment_per_year) # we show all the data because it's not t
display(re_investment_per_year.describe())
re_investment_per_year.plot(
    x=DATE_COLUMN,
    y='re investment',
    title='US real estate total investment per year',
    figsize=(4, 2)
    )
plt.show()
```

	Year	re investment
1	2001	1.560357e+10
2	2002	1.720434e+10
3	2003	2.516201e+10
4	2004	3.021333e+10
5	2005	2.159822e+10
6	2006	2.222218e+10
7	2007	1.412136e+10
8	2008	1.177615e+10
9	2009	1.383911e+10
10	2010	1.104590e+10
11	2011	1.299903e+10
12	2012	1.538165e+10
13	2013	1.659346e+10
14	2014	1.913221e+10
15	2015	2.275452e+10
16	2016	1.895052e+10
17	2017	1.844713e+10
18	2018	2.084145e+10
19	2019	2.721690e+10
20	2020	3.178363e+09

	Year	re investment
count	20.00000	2.000000e+01
mean	2010.50000	1.791407e+10
std	5.91608	6.191910e+09
min	2001.00000	3.178363e+09
25%	2005.75000	1.405080e+10
50%	2010.50000	1.782573e+10
75%	2015.25000	2.175421e+10
max	2020.00000	3.021333e+10

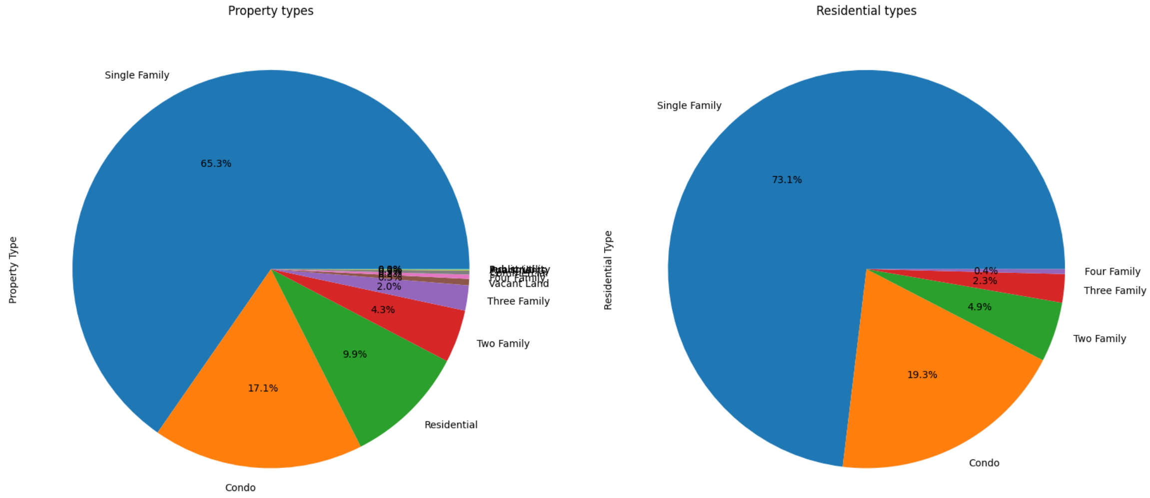
Investment per type per year

In [ ]:
```
def get_types(df:pd.DataFrame, column:str) -> list:
    types = df[column].unique()
    types = [str(x) for x in types]
    return types
def print_types(df: pd.DataFrame, column:str) -> None:
    types = get_types(df, column)
    for i, x in enumerate(types):
        print(f'{i+1}.\t{x}')
print('Real estate properties types:')
print_types(real_estate_sales, 'Property Type')
print()
print('Real estate residential types:')
print_types(real_estate_sales, 'Residential Type')
```

```
Real estate properties types:
1.      Commercial
2.      Residential
3.      Vacant Land
4.      nan
5.      Apartments
6.      Industrial
7.      Public Utility
8.      Condo
9.      Two Family
10.     Three Family
11.     Single Family
12.     Four Family

Real estate residential types:
1.      nan
2.      Single Family
3.      Condo
4.      Two Family
5.      Three Family
6.      Four Family
```

In [ ]:
```
fig, axs = plt.subplots(1, 2, figsize=(20, 20))
real_estate_sales['Property Type'] \
    .value_counts(normalize=True).plot.pie(autopct='%1.1f%%', title='Prop
real_estate_sales['Residential Type'] \
    .value_counts(normalize=True).plot.pie(autopct='%1.1f%%', title='Resi
```

```
Out[ ]: <Axes: title={'center': 'Residential types'}, ylabel='Residential Type'>
```




```
In [ ]: def groupby_type_and_year(df:pd.DataFrame, column:str) -> pd.DataFrame:
            result = pd.DataFrame()
            result['Year'] = real_estate_sales[DATE_COLUMN].unique()
            result = result.sort_values(by=DATE_COLUMN).reset_index(drop=True)
            #
            result = ensure_date_type(result)
            df = ensure_date_type(df)
            #
            for type in get_types(df, column):
                new_column_name = f're {type.upper()} investment'
                result[new_column_name] = 0
                for year in result[DATE_COLUMN]:
                    sales_amount = df[(df[column] == type) & (df[DATE_COLUMN] ==
                    result.loc[result[DATE_COLUMN] == year, new_column_name] = sa
                result = normalize_with_population(result, new_column_name)
            return result

        property_types_annual = groupby_type_and_year(real_estate_sales, 'Propert
        residential_types_annual = groupby_type_and_year(real_estate_sales, 'Resi

        # Drop columns with lot of zeros.
        property_types_annual = keep_columns(property_types_annual, [
            DATE_COLUMN,
            're CONDO investment',
            're TWO FAMILY investment',
            're THREE FAMILY investment',
            're SINGLE FAMILY investment',
            're FOUR FAMILY investment',
        ])
        residential_types_annual = keep_columns(residential_types_annual, [
            DATE_COLUMN,
            're SINGLE FAMILY investment',
            're CONDO investment',
            're TWO FAMILY investment',
            're THREE FAMILY investment',
            're FOUR FAMILY investment',
        ])

        print("Property sales")
        display(property_types_annual)
        display(property_types_annual.describe())
        print("Residential sales")
```

```
display(residential_types_annual)
display(residential_types_annual.describe())

# Show property types
property_types_annual.plot(
    x=DATE_COLUMN,
    y=property_types_annual.columns[1:],
    title='US real estate sales per property type over time',
    )
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
plt.show()

# Show residential types
residential_types_annual.plot(
    x=DATE_COLUMN,
    y=residential_types_annual.columns[1:],
    title='US real estate sales per residential type over time',
    )
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0.)
plt.show()
```

```
Property sales
```

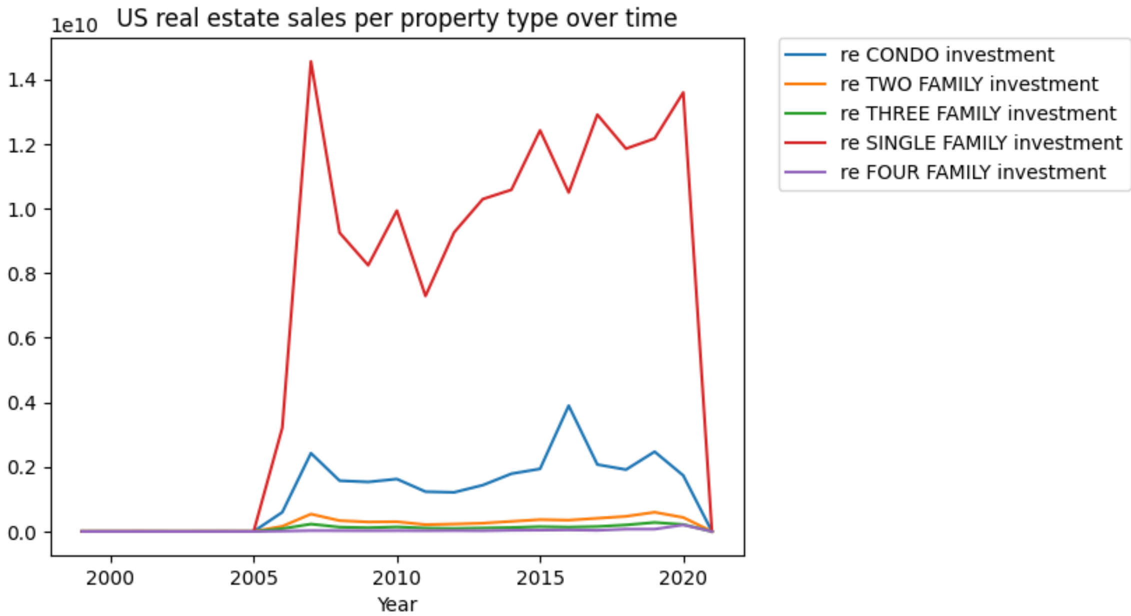
	Year	re CONDO investment	re TWO FAMILY investment	re THREE FAMILY investment	re SINGLE FAMILY investment	re FOUR FAMILY investment
0	1999	9.500000e+04	0.000000e+00	0	0.000000e+00	0
1	2001	8.800000e+04	0.000000e+00	0	2.402711e+06	0
2	2002	0.000000e+00	0.000000e+00	0	0.000000e+00	0
3	2003	0.000000e+00	0.000000e+00	0	1.589000e+05	0
4	2004	6.329000e+05	0.000000e+00	0	1.949900e+06	0
5	2005	2.770000e+05	2.640000e+05	0	0.000000e+00	0
6	2006	5.948589e+08	1.603019e+08	86599217	3.210213e+09	10182700
7	2007	2.423580e+09	5.385773e+08	228334313	1.455175e+10	25293008
8	2008	1.571634e+09	3.353331e+08	134461433	9.249377e+09	23560218
9	2009	1.533074e+09	2.929898e+08	115687933	8.241461e+09	21736964
10	2010	1.622946e+09	3.010015e+08	140404872	9.933565e+09	24317690
11	2011	1.231526e+09	2.110223e+08	104523619	7.290372e+09	21693403
12	2012	1.211207e+09	2.299405e+08	91109852	9.260353e+09	25816807
13	2013	1.433486e+09	2.556605e+08	106807382	1.028991e+10	20942328
14	2014	1.787715e+09	3.111695e+08	122285490	1.057817e+10	35849185
15	2015	1.938384e+09	3.668705e+08	149280615	1.241745e+10	39880680
16	2016	3.894486e+09	3.498937e+08	135213185	1.049482e+10	46846302
17	2017	2.071585e+09	4.077366e+08	152915555	1.290385e+10	34627440
18	2018	1.913916e+09	4.677992e+08	201257041	1.185046e+10	71015671
19	2019	2.469696e+09	5.949037e+08	278538608	1.216468e+10	71852599
20	2020	1.732257e+09	4.329061e+08	216103966	1.359104e+10	202110732
21	2021	0.000000e+00	0.000000e+00	0	0.000000e+00	0

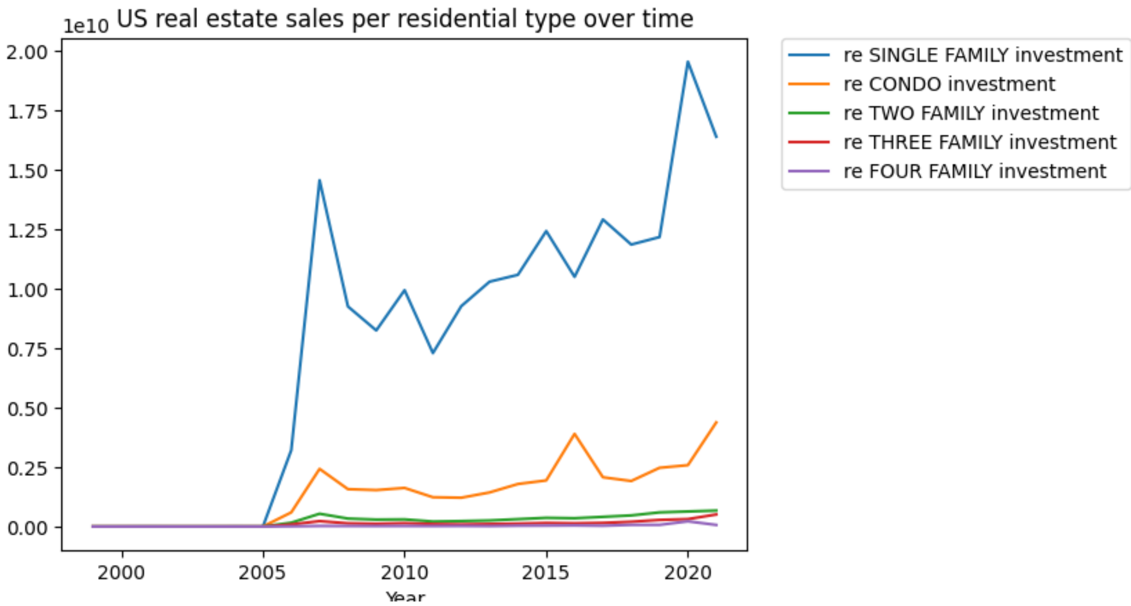
	Year	re CONDO investment	re TWO FAMILY investment	re THREE FAMILY investment	re SINGLE FAMILY investment	re FOUR FAMILY investment
count	22.000000	2.200000e+01	2.200000e+01	2.200000e+01	2.200000e+01	2.200000e+01
mean	2010.454545	1.246884e+09	2.389259e+08	1.028874e+08	7.092363e+09	3.071481e+07
std	6.573593	1.062153e+09	1.941756e+08	8.514759e+07	5.469519e+09	4.391946e+07
min	1999.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	2005.250000	3.659750e+05	6.600000e+04	0.000000e+00	2.063103e+06	0.000000e+00
50%	2010.500000	1.483280e+09	2.743252e+08	1.112477e+08	9.254865e+09	2.264859e+07
75%	2015.750000	1.882366e+09	3.626263e+08	1.470617e+08	1.153239e+10	3.554375e+07
max	2021.000000	3.894486e+09	5.949037e+08	2.785386e+08	1.455175e+10	2.021107e+08

```
Residential sales
```

	Year	re SINGLE FAMILY investment	re CONDO investment	re TWO FAMILY investment	re THREE FAMILY investment	re FOUR FAMILY investment
0	1999	0.000000e+00	9.500000e+04	0.000000e+00	0.000000e+00	0
1	2001	2.402711e+06	8.800000e+04	0.000000e+00	0.000000e+00	0
2	2002	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0
3	2003	1.589000e+05	0.000000e+00	0.000000e+00	0.000000e+00	0
4	2004	1.949900e+06	6.329000e+05	0.000000e+00	0.000000e+00	0
5	2005	0.000000e+00	2.770000e+05	2.640000e+05	0.000000e+00	0
6	2006	3.210213e+09	5.948589e+08	1.603019e+08	8.659922e+07	10182700
7	2007	1.455175e+10	2.423580e+09	5.385773e+08	2.283343e+08	25293008
8	2008	9.249377e+09	1.571634e+09	3.353331e+08	1.344614e+08	23560218
9	2009	8.241461e+09	1.533074e+09	2.929898e+08	1.156879e+08	21736964
10	2010	9.933565e+09	1.622946e+09	3.010015e+08	1.404049e+08	24317690
11	2011	7.290372e+09	1.231526e+09	2.110223e+08	1.045236e+08	21693403
12	2012	9.260353e+09	1.211207e+09	2.299405e+08	9.110985e+07	25816807
13	2013	1.028991e+10	1.433486e+09	2.556605e+08	1.068074e+08	20942328
14	2014	1.057817e+10	1.787715e+09	3.111695e+08	1.222855e+08	35849185
15	2015	1.241745e+10	1.938384e+09	3.668705e+08	1.492806e+08	39880680
16	2016	1.049482e+10	3.894486e+09	3.498937e+08	1.352132e+08	46846302
17	2017	1.290385e+10	2.071585e+09	4.077366e+08	1.529156e+08	34627440
18	2018	1.185046e+10	1.913916e+09	4.677992e+08	2.012570e+08	71015671
19	2019	1.216468e+10	2.469696e+09	5.949037e+08	2.785386e+08	71852599
20	2020	1.953491e+10	2.579188e+09	6.332712e+08	3.134679e+08	219821632
21	2021	1.638224e+10	4.375425e+09	6.710182e+08	5.073493e+08	68068605

	Year	re SINGLE FAMILY investment	re CONDO investment	re TWO FAMILY investment	re THREE FAMILY investment	re FOUR FAMILY investment
count	22.000000	2.200000e+01	2.200000e+01	2.200000e+01	2.200000e+01	2.200000e+01
mean	2010.454545	8.107186e+09	1.484264e+09	2.785342e+08	1.303744e+08	3.461387e+07
std	6.573593	5.992677e+09	1.238747e+09	2.187378e+08	1.234736e+08	4.731333e+07
min	1999.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	2005.250000	8.043554e+08	1.491894e+08	4.027347e+07	2.164980e+07	2.545675e+06
50%	2010.500000	9.596959e+09	1.552354e+09	2.969957e+08	1.189867e+08	2.393895e+07
75%	2015.750000	1.208612e+10	2.038284e+09	3.975201e+08	1.520068e+08	3.887281e+07
max	2021.000000	1.953491e+10	4.375425e+09	6.710182e+08	5.073493e+08	2.198216e+08





we will discard residential real estate sales because it is very similar to property sales.

In [ ]:
```
real_estate = merge_by_year([
    re_sales_per_year, property_types_annual, re_investment_per_year,
    ])
```

```
# Review if final real estate dataframe were correctly merged
real_estate.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20 entries, 1 to 20
Data columns (total 8 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Year                        20 non-null     int64
 1   re sales                    20 non-null     float64
 2   re CONDO investment         20 non-null     float64
 3   re TWO FAMILY investment    20 non-null     float64
 4   re THREE FAMILY investment  20 non-null     int64
 5   re SINGLE FAMILY investment 20 non-null     float64
 6   re FOUR FAMILY investment   20 non-null     int64
 7   re investment               20 non-null     float64
dtypes: float64(5), int64(3)
memory usage: 1.4 KB
```

Reviewing the U.S. crude oil production

U.S. field production of crude oil data were obtained from [U.S. Energy Information Administration](#).

In [ ]:
```
crude = pd.read_csv(f'{DATASETS_FOLDER}/U.S._Field_Production_of_Crude_Oi
#
print('# Original data')
display(crude.tail())
#
crude = cut_add_years(crude)
crude = crude.rename(columns={
    'U.S. Field Production of Crude Oil Thousand Barrels per Day': 'Crude
})
crude = normalize_with_population(crude, 'Crude Oil Production')
#
print('# Cleaned data')
display(crude) # we show all the data because it's not too much
display(crude.describe())
crude.plot(x='Year', y='Crude Oil Production', title='U.S. Field Producti
plt.show()
```

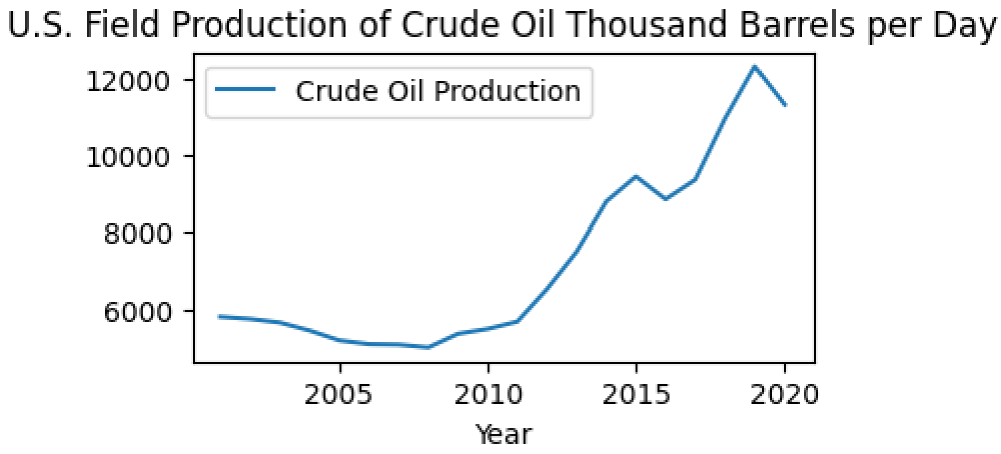
```
# Original data
```

	Year	U.S. Field Production of Crude Oil Thousand Barrels per Day
159	1863	7
160	1862	8
161	1861	6
162	1860	1
163	1859	0

```
# Cleaned data
```

	Year	Crude Oil Production
142	2001	5801
143	2002	5744
144	2003	5649
145	2004	5441
146	2005	5184
147	2006	5086
148	2007	5074
149	2008	5000
150	2009	5357
151	2010	5484
152	2011	5674
153	2012	6524
154	2013	7497
155	2014	8793
156	2015	9442
157	2016	8848
158	2017	9359
159	2018	10953
160	2019	12315
161	2020	11318

	Year	Crude Oil Production
count	20.00000	20.000000
mean	2010.50000	7227.150000
std	5.91608	2393.169299
min	2001.00000	5000.000000
25%	2005.75000	5420.000000
50%	2010.50000	5772.500000
75%	2015.25000	8975.750000
max	2020.00000	12315.000000



Reviewing book publishing

Book dataset were obtained from scostap - Goodreads Best Book Ever dataset, as the data was scraped by the author, we will analyze outliers and more.

In [ ]:
```
book = pd.read_csv(f'{DATASETS_FOLDER}/books_1.Best_Books_Ever.csv')
#
print('# Original data')
display(book.tail())
#
book = keep_columns(book, [
    'bookFormat', 'pages', 'publishDate', 'rating', 'likedPercent', 'pric
    ])
book = book.dropna()
# Format date
book = book[book['publishDate'].str.match(r'\d{1,2}/\d{1,2}/\d{2}')]
book['publishDate'] = pd.to_datetime(book['publishDate'],format="%m/%d/%y
book['publishDate'] = book['publishDate'].dt.strftime('%Y-%m-%d')
# Ensure that those columns are numeric and not null
for col in ['pages', 'rating', 'likedPercent', 'price']:
    book = book[pd.to_numeric(book[col], errors='coerce').notnull()]
    book[col] = book[col].astype(float)
# Show final columns
print('# Cleaned data')
display(book.tail())
display(book.describe())
```

```
# Original data
```

	bookId	title	series	author	rating	description	language	
52473	11492014-fractured	Fractured	Fateful #2	Cheri Schmidt (Goodreads Author)	4.00	The Fateful Trilogy continues with Fractured. ...	English	29400126
52474	11836711-anasazi	Anasazi	Sense of Truth #2	Emma Michaels	4.19	'Anasazi', sequel to 'The Thirteenth Chime' by...	English	99999999
52475	10815662-marked	Marked	Soul Guardians #1	Kim Richardson (Goodreads Author)	3.70	--READERS FAVORITE AWARDS WINNER 2011--Sixteen...	English	97814610
52476	11330278-wayward-son	Wayward Son	NaN	Tom Pollack (Goodreads Author), John Loftus (G...	3.85	A POWERFUL TREMOR UNEARTHS AN ANCIENT SECRETBu...	English	97814507
52477	10991547-daughter-of-helaman	Daughter of Helaman	Stripling Warrior #1	Misty Moncur (Goodreads Author)	4.02	Fighting in Helaman's army is Keturah's deepes...	English	97815995

5 rows × 25 columns

```
# Cleaned data
```

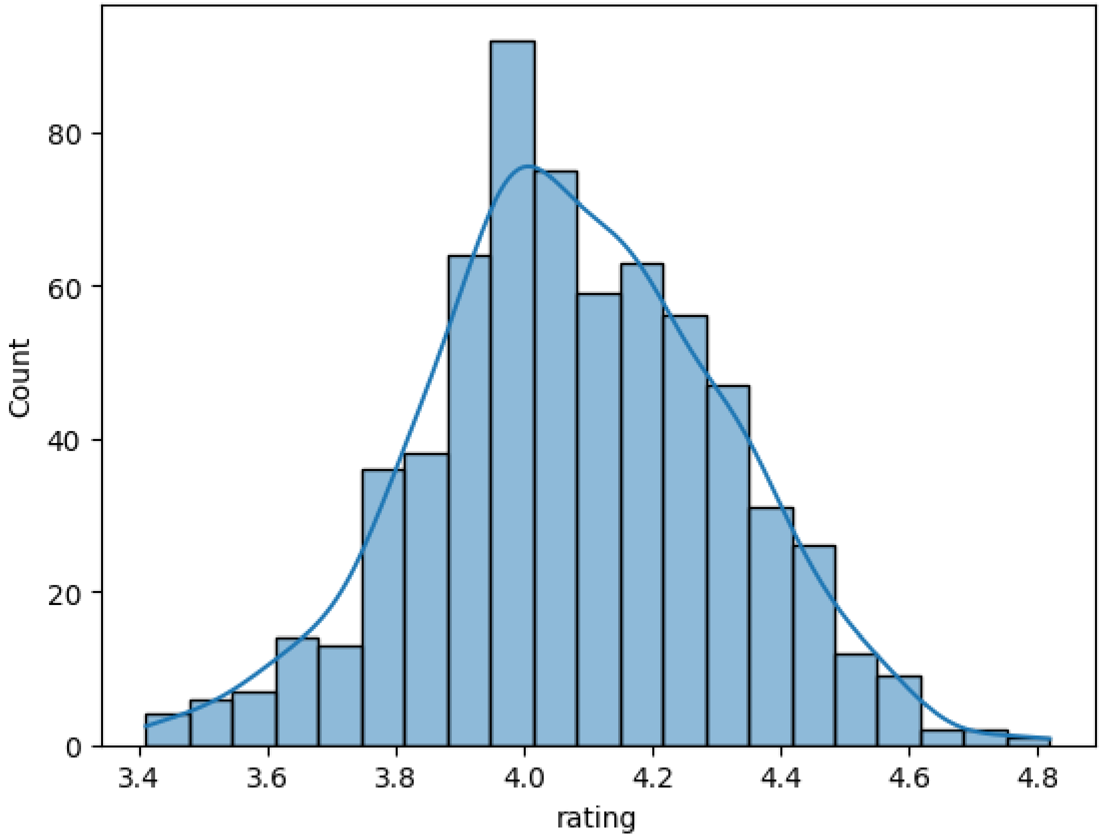
	bookFormat	pages	publishDate	rating	likedPercent	price
814	Mass Market Paperback	357.0	2008-04-29	4.30	97.0	2.86
815	Paperback	515.0	2005-09-22	3.65	86.0	2.86
816	Paperback	416.0	2001-02-01	4.17	95.0	3.55
818	Hardcover	516.0	2014-10-07	4.41	97.0	6.52
819	Hardcover	528.0	2010-04-27	4.40	97.0	6.50

	pages	rating	likedPercent	price
count	657.000000	657.000000	657.000000	657.000000
mean	423.127854	4.076514	92.576865	6.025403
std	289.973231	0.233532	3.742140	7.746120
min	26.000000	3.410000	78.000000	0.850000
25%	272.000000	3.930000	91.000000	2.900000
50%	369.000000	4.060000	93.000000	4.180000
75%	503.000000	4.230000	95.000000	6.270000
max	4100.000000	4.820000	99.000000	110.670000

showing distribution of data

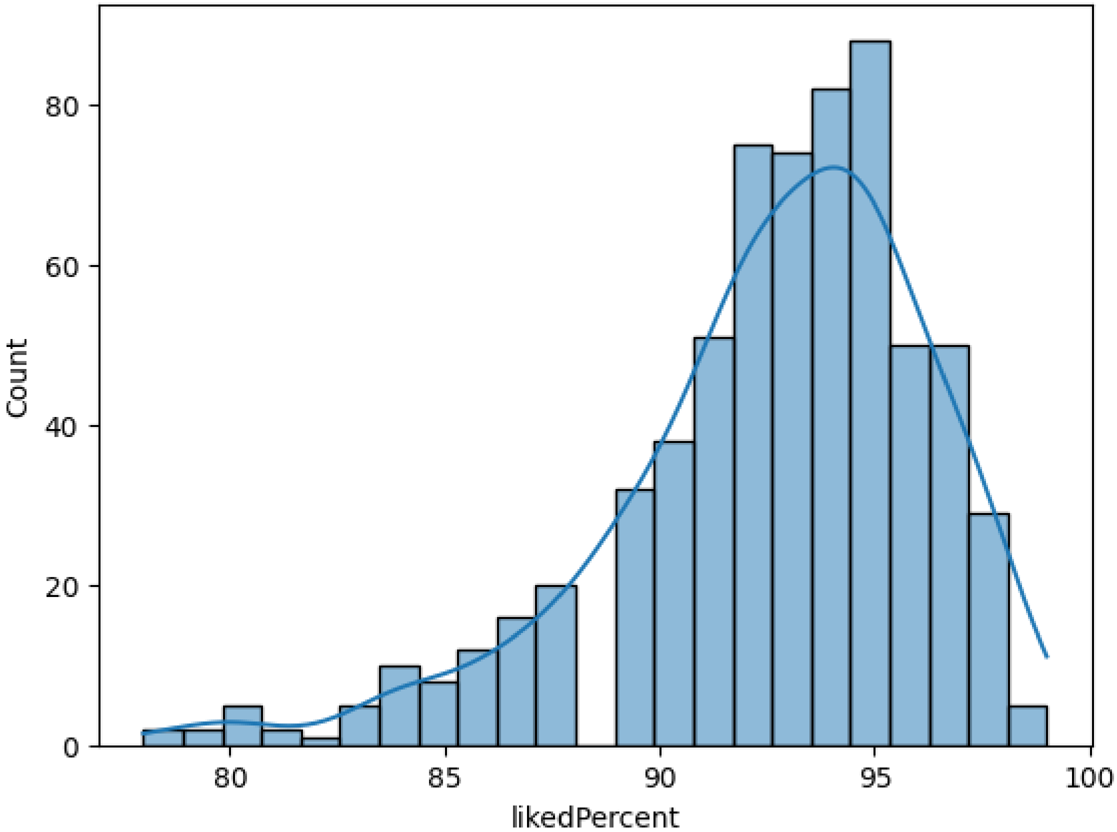
In [ ]:
```
# NOTE: sns.hisplot only shows one plot per cell
sns.histplot(book['rating'], kde=True)
```

Out[ ]: <Axes: xlabel='rating', ylabel='Count'>



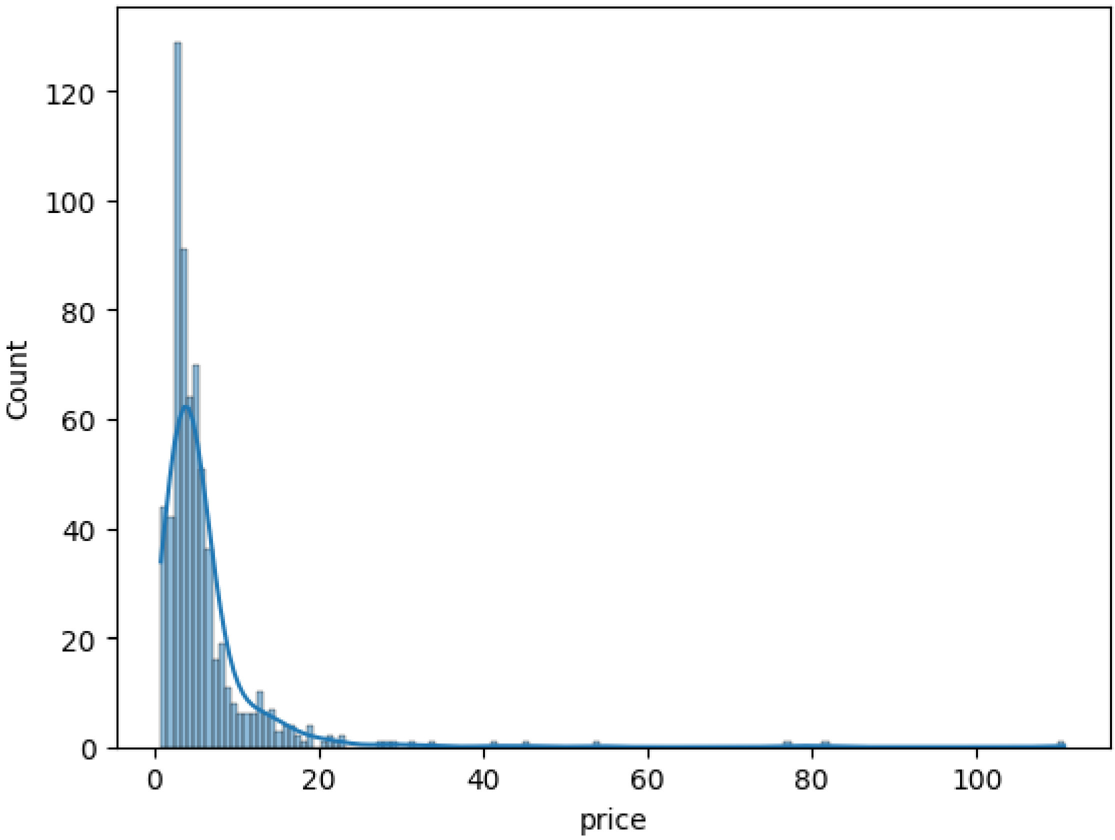
In [ ]:
```
sns.histplot(book['likedPercent'], kde=True)
```

Out[ ]: <Axes: xlabel='likedPercent', ylabel='Count'>



In [ ]:
```
sns.histplot(book['price'], kde=True)
```

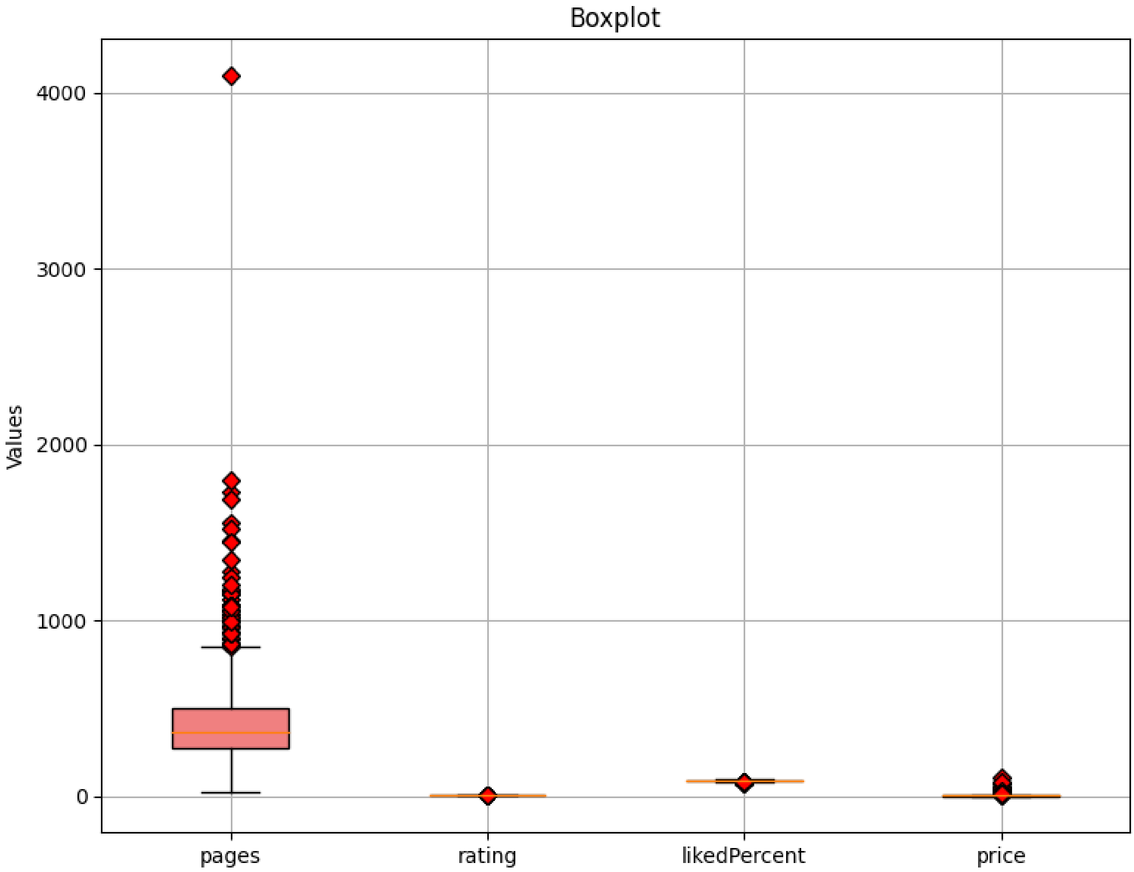
Out[ ]: <Axes: xlabel='price', ylabel='Count'>



Treating outliers

In [ ]:
```
print('# Outliers')

fig, ax1 = plt.subplots(nrows=1, ncols=1, figsize=(9, 7))
bplot = ax1.boxplot(
    book.select_dtypes(include = ["float64"]),
    vert=True,
    patch_artist=True,
    labels=['pages','rating', 'likedPercent', 'price'],
    flierprops=dict(markerfacecolor='r', marker='D')
    )
ax1.set_title('Boxplot')

colors = ['lightcoral', 'mediumpurple', 'gold','aquamarine']

for patch, color in zip(bplot['boxes'], colors):
    patch.set_facecolor(color)

for ax in [ax1]:
    ax.yaxis.grid(True)
    ax.xaxis.grid(True)
    ax.set_ylabel('Values')

plt.show()
```

```
# Outliers
```



In [ ]:
```
# Removing outliers using Z score

def show_min_max(df:pd.DataFrame, column:str) -> None:
    print(f'\tmin {column}: {df[column].min()}\tmax {column}: {df[column]

threshold = 3
for column in ['pages', 'rating', 'likedPercent', 'price']:
```

```
    print('')
    print(f'Outliers for {column}')
    z = np.abs(stats.zscore(book['pages']))
    display(z)
    print('Before removing outliers')
    show_min_max(book, 'pages')
    book = book[(z < threshold)]
    print('After removing outliers')
    show_min_max(book, 'pages')
```

```
Outliers for pages
0      0.169551
1      1.542255
4      0.268754
5      0.444766
6      0.973686
         ...
814    0.228222
815    0.317071
816    0.024600
818    0.320522
819    0.361937
Name: pages, Length: 657, dtype: float64
Before removing outliers
        min pages: 26.0 max pages: 4100.0
After removing outliers
        min pages: 26.0 max pages: 1276.0

Outliers for rating
0      0.134665
1      2.142164
4      0.448313
5      0.682423
6      1.204225
         ...
814    0.212702
815    0.512579
816    0.058131
818    0.517169
819    0.572254
Name: pages, Length: 648, dtype: float64
Before removing outliers
        min pages: 26.0 max pages: 1276.0
After removing outliers
        min pages: 26.0 max pages: 1049.0

Outliers for likedPercent
0      0.068177
1      2.547646
4      0.601600
5      0.870566
6      1.296981
         ...
814    0.157832
815    0.675434
816    0.153324
818    0.680708
819    0.743994
Name: pages, Length: 634, dtype: float64
```

```
Before removing outliers
        min pages: 26.0 max pages: 1049.0
After removing outliers
        min pages: 26.0 max pages: 936.0

Outliers for price
0      0.012310
1      2.858521
4      0.722762
5      1.017948
6      1.360906
         ...
814    0.110705
815    0.803793
816    0.230785
818    0.809581
819    0.879037
Name: pages, Length: 623, dtype: float64
Before removing outliers
        min pages: 26.0 max pages: 936.0
After removing outliers
        min pages: 26.0 max pages: 870.0
```

Analizing the impact of computing advances on real estate sales

Analizing correlations between computing advances and real estate sales.

We will ignore correlations between computer advances columns and years, only focus on computer advances vs real estate correlations.

Analizing correlations

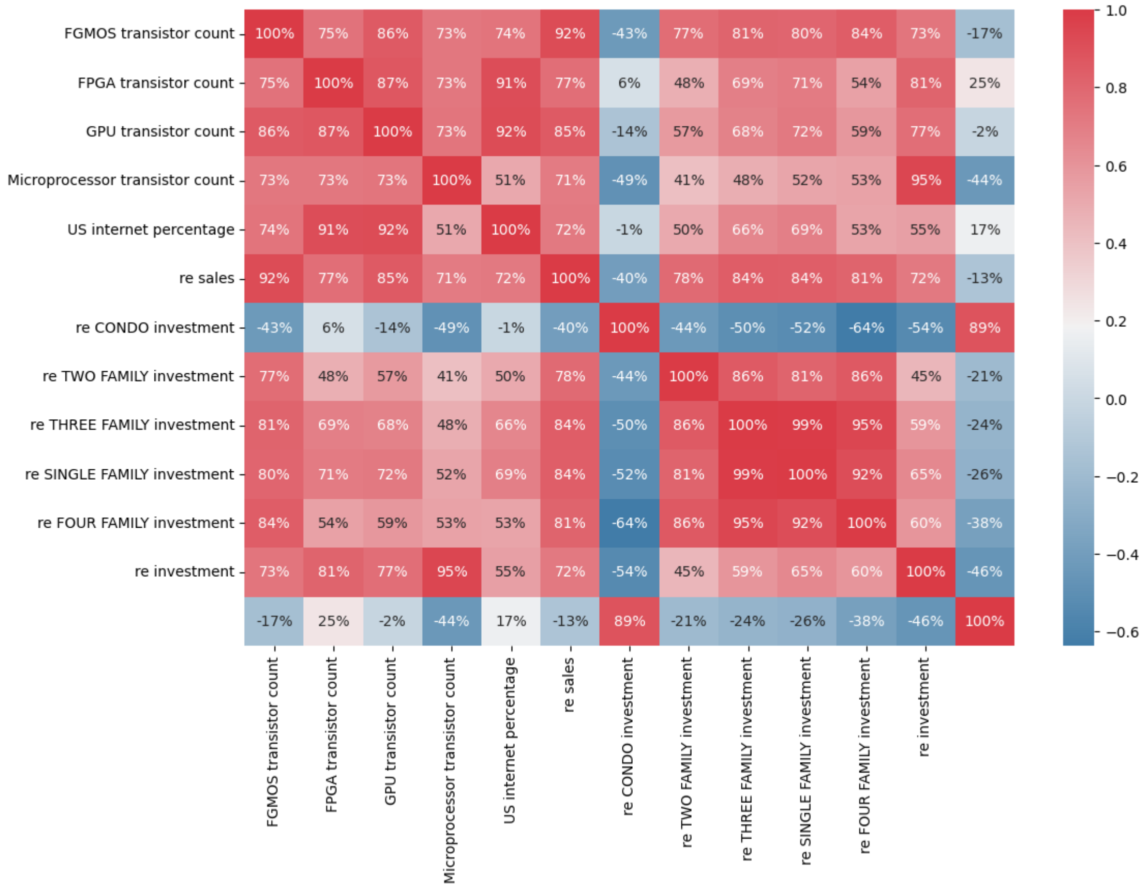
In [ ]:

```
computing_and_real_estate = merge_by_year([computer_advances, real_estate
numeric_df = computing_and_real_estate.select_dtypes(include=['float64',
columns_to_analize_correlation = numeric_df.columns[1:]
```

In [ ]:

```
corr = computing_and_real_estate.corr()
plt.subplots(figsize=(12,8))
sns.heatmap(
    corr,
    xticklabels=columns_to_analize_correlation,
    yticklabels=columns_to_analize_correlation,
    annot=True,
    fmt='.0%',
    cmap=sns.diverging_palette(240, 10, as_cmap=True)
    )
```

Out[ ]: <Axes: >



We can see a high correlation on "Microprocessor transistor count" vs "re investment"

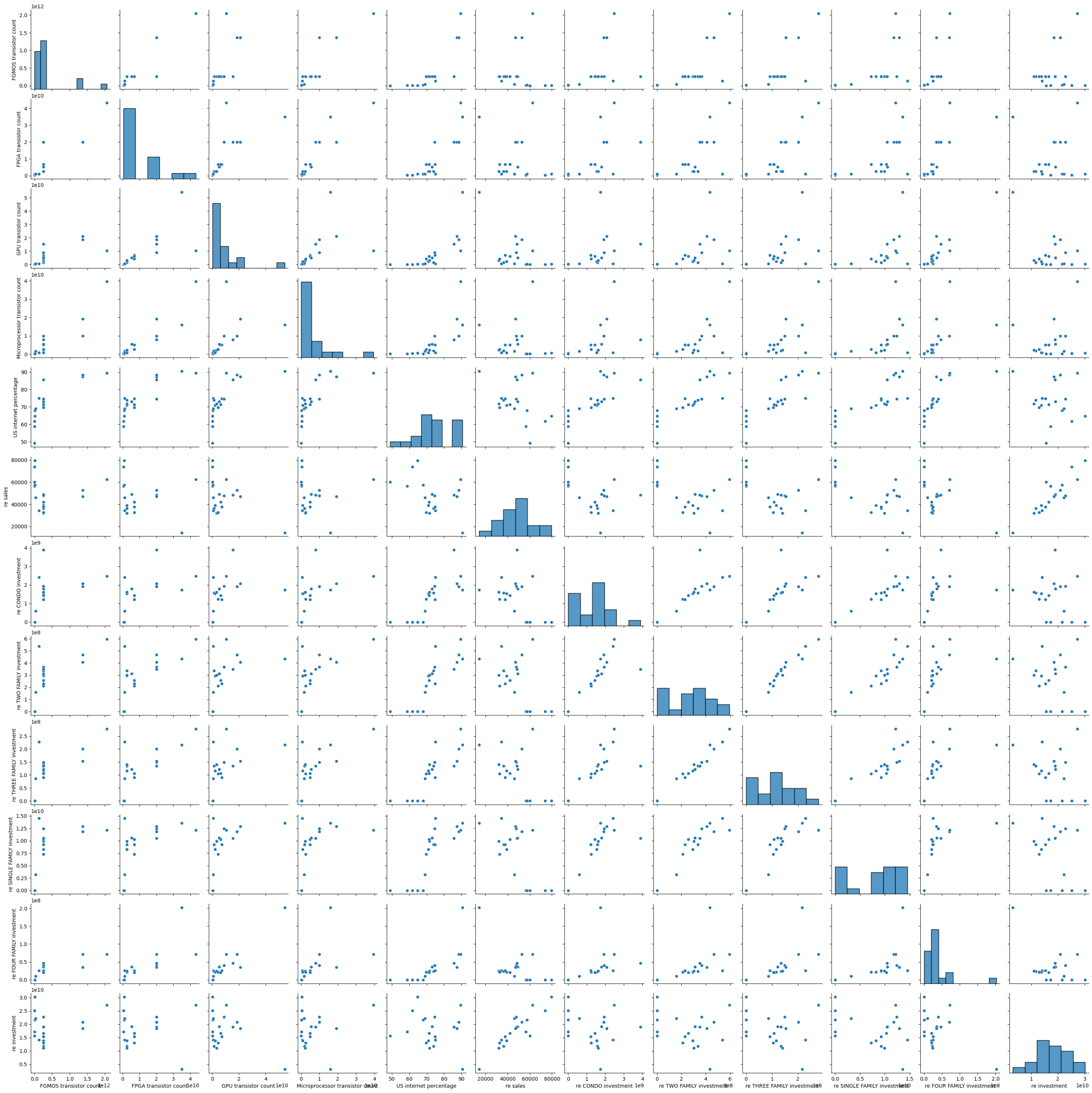
In [ ]:
```
print("Variables most correlated with real estate total investment")
display(corr['re investment'].abs().sort_values(ascending=False))
print("Variables most correlated with real estate total sales")
display(corr['re sales'].abs().sort_values(ascending=False))
```

```
Variables most correlated with real estate total investment
re investment                      1.000000
re sales                           0.891257
re FOUR FAMILY investment          0.463065
GPU transistor count               0.441144
re SINGLE FAMILY investment        0.381849
re THREE FAMILY investment         0.263131
FGMOS transistor count             0.245910
re TWO FAMILY investment           0.243688
re CONDO investment                0.205083
Year                               0.174011
Microprocessor transistor count    0.167502
US internet percentage             0.133680
FPGA transistor count              0.018511
Name: re investment, dtype: float64
Variables most correlated with real estate total sales
```

```
re sales                             1.000000
re investment                        0.891257
re SINGLE FAMILY investment          0.635902
re FOUR FAMILY investment            0.539678
re THREE FAMILY investment           0.521715
re TWO FAMILY investment             0.501825
GPU transistor count                 0.487257
re CONDO investment                  0.435862
Year                                 0.428682
US internet percentage               0.399518
FPGA transistor count                0.142902
FGMOS transistor count               0.056822
Microprocessor transistor count      0.008890
Name: re sales, dtype: float64
```

We can see that the most correlated computing advance with real estate sales and investment is the "GPU transistor count" with 0.48 correlation, note that this is a low correlation, ideal correlation should be close to 1 or -1.

In [ ]:
```
pp = sns.pairplot(
    numeric_df,
    x_vars=columns_to_analize_correlation,
    y_vars=columns_to_analize_correlation
    )
```



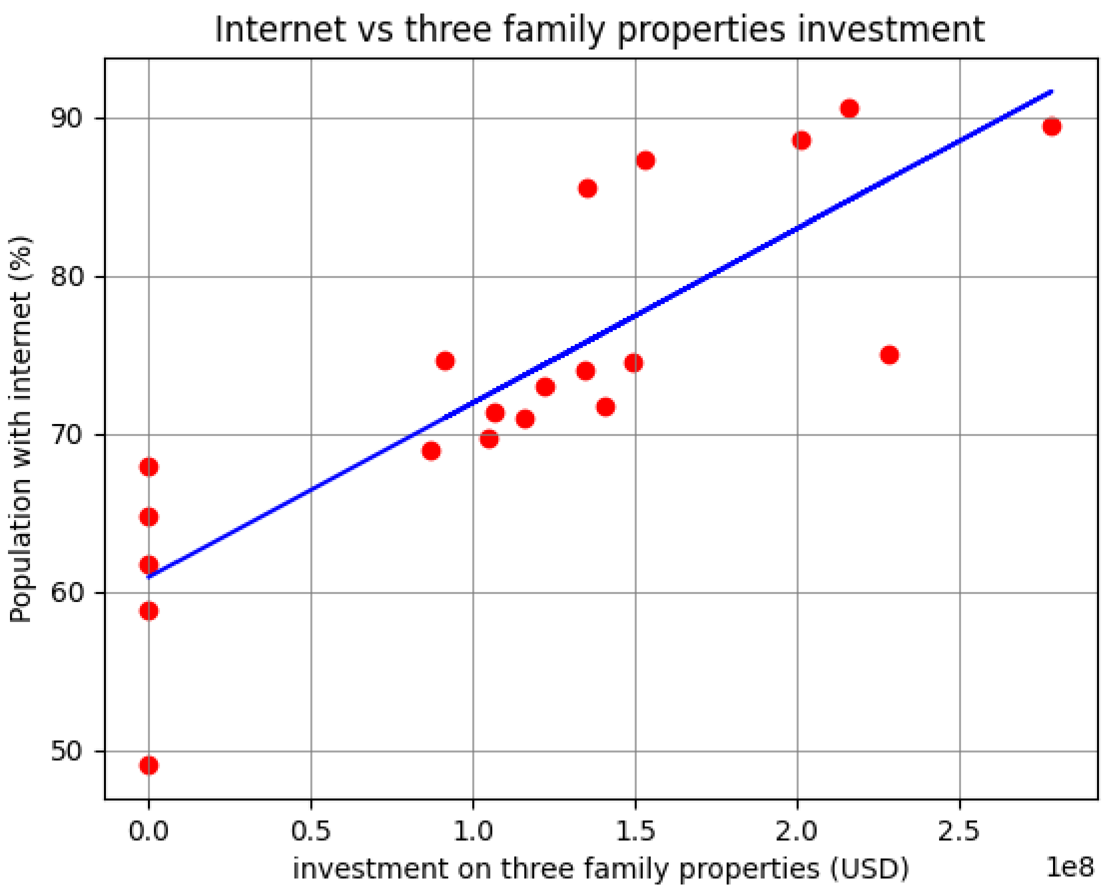
On a first look we can see correlations in multiple columns, some of them are:

- "US internet percentage" vs "re THREE FAMILY investment"
- "Microprocessor transistor count" vs "re SINGLE FAMILY investment"

Also we can see very clear correlation between real estate columns but that is out of scope of this research.

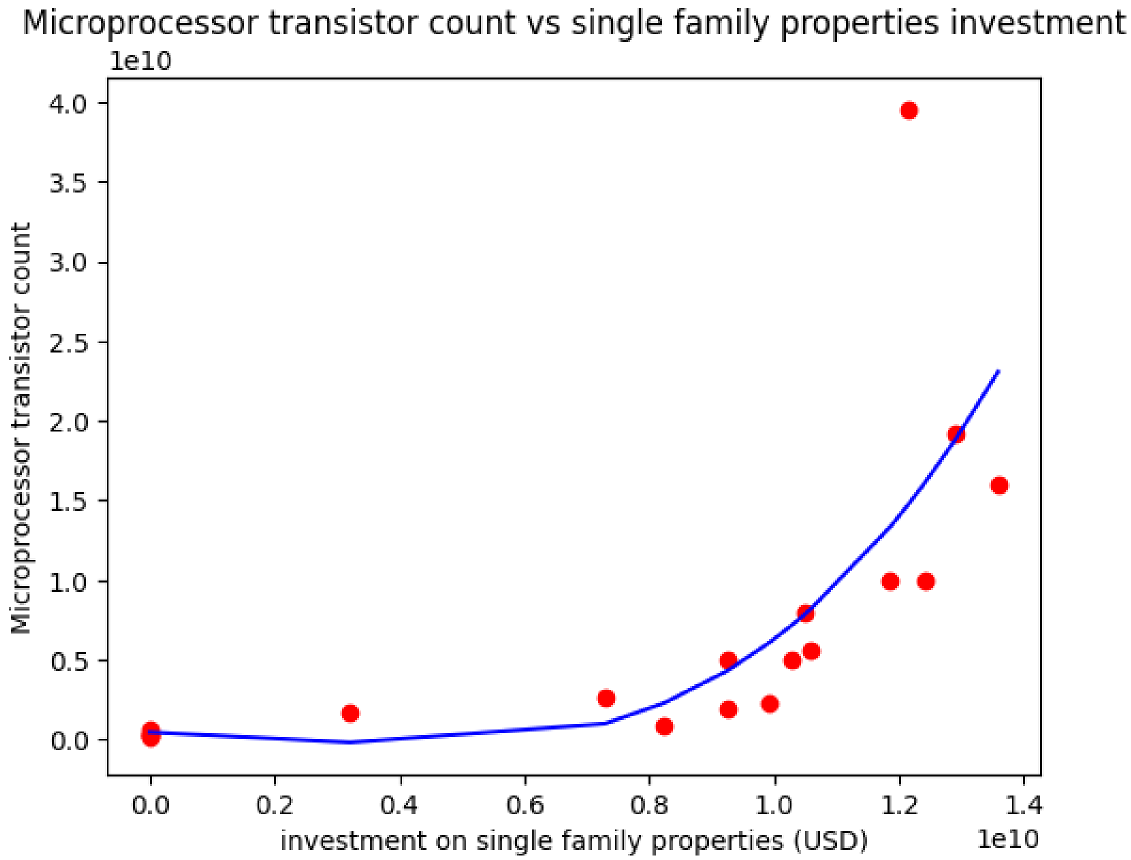
Let's see these correlations in deep and try to do some predictions using Sklearn.

In [ ]:
```
# Review in deep "US internet percentage" vs "re THREE FAMILY investment"
X = computing_and_real_estate['re THREE FAMILY investment'].values.reshap
y = computing_and_real_estate['US internet percentage'].values.reshape(-1
#
lin_reg = LinearRegression()
lin_reg.fit(X,y)
#
plt.scatter(X, y, color = "red")
plt.plot(X, lin_reg.predict(X), color = "blue")
plt.title("Internet vs three family properties investment")
plt.xlabel("investment on three family properties (USD)")
plt.ylabel("Population with internet (%)")
plt.grid(color='gray', linestyle='-', linewidth=0.5)
plt.show()
```



In [ ]:
```
# Review in deep "Microprocessor transistor count" vs "re SINGLE FAMILY i
#
# Remove this value (it's only one row) to get a better prediction
computing_and_real_estate = computing_and_real_estate[computing_and_real_
# Sort X axis to avoid an horrible polynomial prediction
```

```
computing_and_real_estate = computing_and_real_estate.sort_values(by=['re
#
y = computing_and_real_estate['Microprocessor transistor count'].values.r
X = computing_and_real_estate['re SINGLE FAMILY investment'].values.resha
#
lin_reg=LinearRegression()
lin_reg.fit(X,y)
poly_reg=PolynomialFeatures(degree=3)
X_poly=poly_reg.fit_transform(X)
poly_reg.fit(X_poly,y)
lin_reg2=LinearRegression()
lin_reg2.fit(X_poly,y)
#
plt.scatter(X,y,color='red')
plt.plot(X,lin_reg2.predict(poly_reg.fit_transform(X)),color='blue')
plt.title('Microprocessor transistor count vs single family properties in
plt.xlabel('investment on single family properties (USD)')
plt.ylabel('Microprocessor transistor count')
plt.show()
```



We have a clue that the GPU advances has the most impact on real estate sales and investments based on the correlation analysis, but now let's go more deep and try to get how much has impacted each computer technology using multiple linear regression.

Let's start analizing the computer advances with real estate INVESTMENT.

In [ ]:
```
df = computing_and_real_estate
df = df.dropna()
#
X = keep_columns(
    df,
    df.columns[1:-1].tolist()
```

```
    )
y = df['re investment'].values
#
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
regressor = LinearRegression()
regressor.fit(X_train, y_train)
df = df.drop(columns=['re investment', 'Year'], axis=1)
df = df.T
df = df.index
coeff_df = pd.DataFrame(regressor.coef_, df, columns=['Coefficient'])
coeff_df
```

Out[ ]:

	Coefficient
FGMOS transistor count	-2.224972e-02
FPGA transistor count	-6.263642e-02
GPU transistor count	8.761105e-03
Microprocessor transistor count	9.342330e-01
US internet percentage	1.255950e+09
re sales	2.285856e+05
re CONDO investment	-8.669827e+00
re TWO FAMILY investment	-5.435286e+01
re THREE FAMILY investment	4.441187e+01
re SINGLE FAMILY investment	4.920638e-01
re FOUR FAMILY investment	2.343417e+02

We can see that for each percentage of population with access to the internet, the real estate investment increases 1.2x10^9 USD, this make the internet the most important computing advance for real estate investment.

Let's see the same analysis but for real estate SALES.

In [ ]:

```
df = computing_and_real_estate
df = df.dropna()
#
X = keep_columns(
    df,
    df.columns[1:-1].tolist()
    )
y = df['re sales'].values
#
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
regressor = LinearRegression()
regressor.fit(X_train, y_train)
df = df.drop(columns=['re sales', 'Year'], axis=1)
df = df.T
df = df.index
coeff_df = pd.DataFrame(regressor.coef_, df, columns=['Coefficient'])
coeff_df
```

Out[ ]:

	Coefficient
FGMOS transistor count	1.944215e-19
FPGA transistor count	4.884932e-17
GPU transistor count	-2.794747e-17
Microprocessor transistor count	-2.726835e-17
US internet percentage	5.135014e-08
re CONDO investment	1.000000e+00
re TWO FAMILY investment	-8.055581e-17
re THREE FAMILY investment	-9.319453e-17
re SINGLE FAMILY investment	-1.298297e-14
re FOUR FAMILY investment	-5.123188e-17
re investment	2.051382e-14

Again, we can see that the tecnology that has the better coefficient is internet

Conclusion

Analizing the real estate business analytics in conjunction with computing advances, we can see that internet was the technology with most impact on sales and investment, also we have seen that the increment on microprocessor transistors has a correlation with investments made on single family properties.

But this is not very conclusive because other factors as the politics taken by the government and the boom of 2008 could distort the results.

We should take a look into other industries as the crude oil production or book publishing to see if we can get more conclusive results of how much has impacted each computing advance on conventional businesses and markets.

to be continued ...