

```
%pip install -U dataprep
```

```
Requirement already satisfied: cloudpickle>=1.1.1 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: fsspec>=0.6.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: toolz>=0.8.2 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: partd>=0.3.10 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: Werkzeug>=2.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: itsdangerous>=2.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: importlib-metadata>=3.6.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: click>=8.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: Six in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: ipykernel>=4.5.1 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: traitlets>=4.3.1 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: nbformat>=4.2.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: jupyterlab-widgets>=1.0.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: ipython-genutils<=0.2.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: ipython>=4.0.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: widgetsnbextension<=3.6.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: jupyter-client in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: prompt-toolkit<2.0.0,>=1.0.4 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: simplegeneric>0.8 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: pexpect in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: pygments in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: decorator in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: ply in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: jupyter-core in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: pyparsing!=0.17.0,!0.17.1,!0.17.2,>=0.14.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: importlib-resources>=1.4.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: joblib in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: locket in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: wcwidth in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: greenlet!=0.4.17 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: asttokens<3.0.0,>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: pure_eval<1.0.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: executing<0.9.0,>=0.8.3 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: notebook>=4.4.1 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: nbconvert in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: Send2Trash in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: terminado>=0.8.1 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: pyzmq>=13 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: ptyprocess in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: idna>=2.0 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: cycycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: entrypoints>=0.2.2 in /usr/local/lib/python3.7/dist-packages (from dataprep)
Requirement already satisfied: bleach in /usr/local/lib/python3.7/dist-packages (from dataprep)
```

```
Requirement already satisfied: testpath in /usr/local/lib/python3.7/dist-packages (tr
Requirement already satisfied: mistune<2,>=0.8.1 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: pandocfilters>=1.4.1 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: defusedxml in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: webencodings in /usr/local/lib/python3.7/dist-packages
```

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load
```

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

```
# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files unc
```

```
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the
```

```
from dataprep.eda import create_report
from sklearn.model_selection import train_test_split
from sklearn.metrics import auc, classification_report, roc_auc_score
from sklearn.ensemble import RandomForestClassifier
import warnings
warnings.filterwarnings('ignore')
```

## ▼ Reading Data

```
train=pd.read_csv('/content/beginner.csv')
```

```
train.head()
```

	YEAR	SERIAL	MONTH	HWTFINL	CPSID	ASECFLAG	HFLAG	ASECWTH	REGION	ST
0	2015	16566	3	NaN	0	1.0	NaN	1671.32	12	
1	2020	49554	6	1930.4505	20200504991400	NaN	NaN	NaN	33	

```
print("Shape of Train Dataset: "+str(train.shape))
```

```
Shape of Train Dataset: (54737, 29)
```

4	2018	31356	3	NaN	20170102597500	1.0	NaN	1719.16	22
---	------	-------	---	-----	----------------	-----	-----	---------	----

If we exclude the Column we plan to predict, we have 28 columns to use as features and we are going to predict the INCWAGE column

### ▼ Let's check the type of these columns

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54737 entries, 0 to 54736
Data columns (total 29 columns):
#   Column      Non-Null Count  Dtype
---  -
0   YEAR        54737 non-null  int64
1   SERIAL      54737 non-null  int64
2   MONTH       54737 non-null  int64
3   HWTFINL     30160 non-null  float64
4   CPSID       54737 non-null  int64
5   ASECFLAG    26695 non-null  float64
6   HFLAG       2028 non-null   float64
7   ASECWTH     24577 non-null  float64
8   REGION      54737 non-null  int64
9   STATEFIP    54737 non-null  int64
10  NFAMS       54737 non-null  int64
11  PERNUM      54737 non-null  int64
12  WTFINL      30160 non-null  float64
13  CPSIDP      54737 non-null  int64
14  ASECWT      24577 non-null  float64
15  AGE         54737 non-null  int64
16  SEX         54737 non-null  int64
17  RACE        54737 non-null  int64
18  MARST       54737 non-null  int64
19  BPL         54737 non-null  int64
20  EMPSTAT     54737 non-null  int64
21  OCC         54737 non-null  int64
22  UHRSWORKT   54737 non-null  int64
23  WKSTAT      54737 non-null  int64
24  JOBCERT     30160 non-null  float64
25  EDUC        54737 non-null  int64
26  EDDIPGED    30160 non-null  float64
27  INCWAGE     24577 non-null  float64
```

```

28 OINCWAGE    24577 non-null float64
dtypes: float64(10), int64(19)
memory usage: 12.1 MB

```

We have 8 columns considered as Categorical features and the rest are numerical features

### ▼ Let's check for missing values

```
train.isna().sum()
```

```

YEAR          0
SERIAL        0
MONTH         0
HWTFINL      24577
CPSID         0
ASECFLAG     28042
HFLAG        52709
ASECWTH      30160
REGION        0
STATEFIP      0
NFAMS         0
PERNUM        0
WTFINL       24577
CPSIDP        0
ASECWT       30160
AGE           0
SEX           0
RACE          0
MARST         0
BPL           0
EMPSTAT       0
OCC           0
UHRSWORKT    0
WKSTAT        0
JOBCERT      24577
EDUC          0
EDDIPGED     24577
INCWAGE      30160
OINCWAGE     30160
dtype: int64

```

### ▼ To have quick EDA we will use a powerful library that provides insights on the dataset

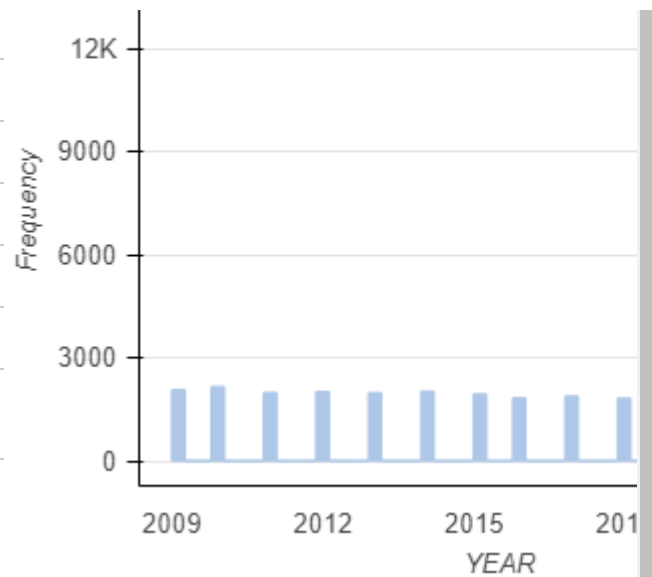
```
report = create_report(train, title='My Report')
```

report



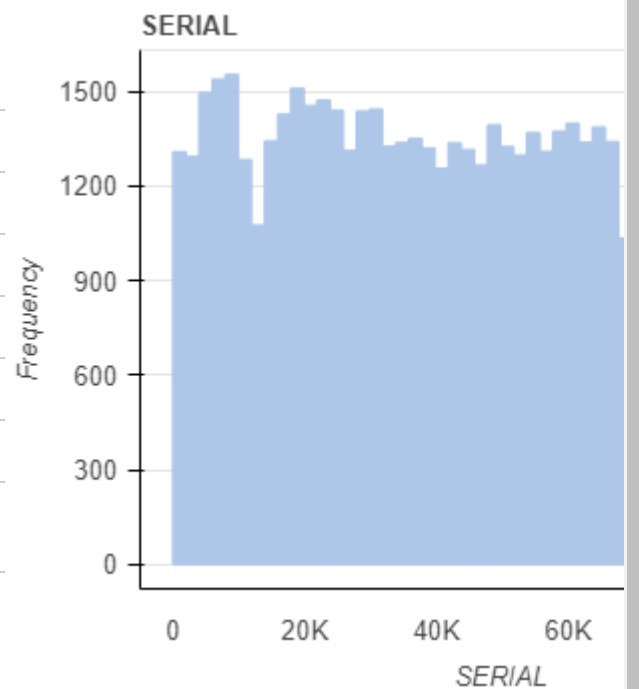
Approximate Distinct Count	14
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Infinte	0
Infinte (%)	0.0%
Memory Size	855.3 KB

Mean	2017.8782
Minimum	2009
Maximum	2022
Zeros	0
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%



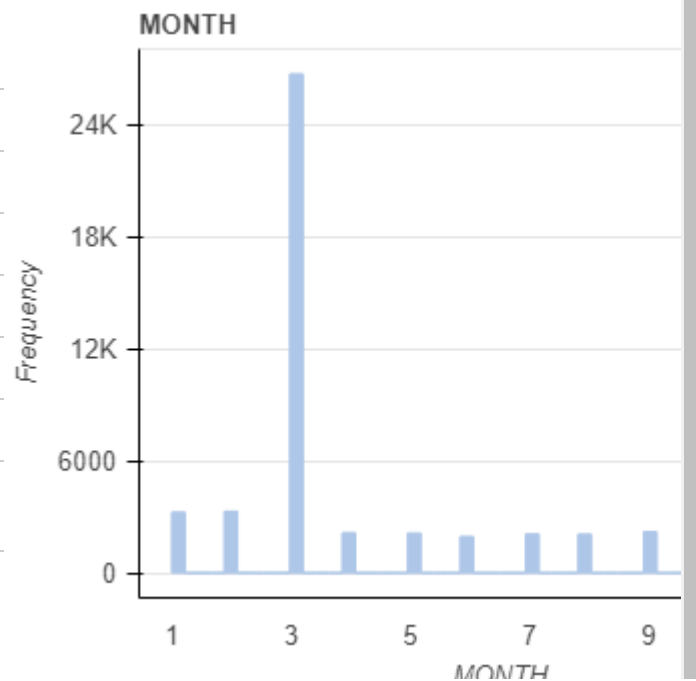
Approximate Distinct Count	40584
Approximate Unique (%)	74.1%
Missing	0
Missing (%)	0.0%
Infinte	0
Infinte (%)	0.0%
Memory Size	855.3 KB

Mean	40716.2568
Minimum	5
Maximum	99417
Zeros	0
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%

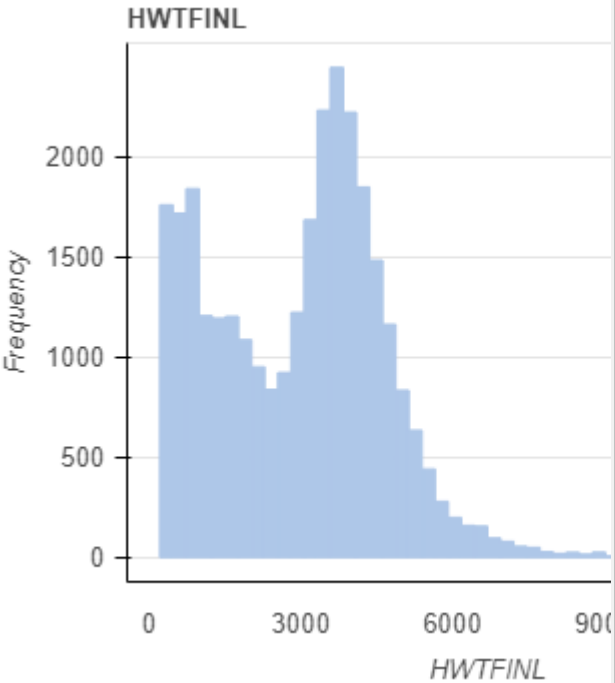


Approximate Distinct Count	12
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Infinte	0
Infinte (%)	0.0%
Memory Size	855.3 KB

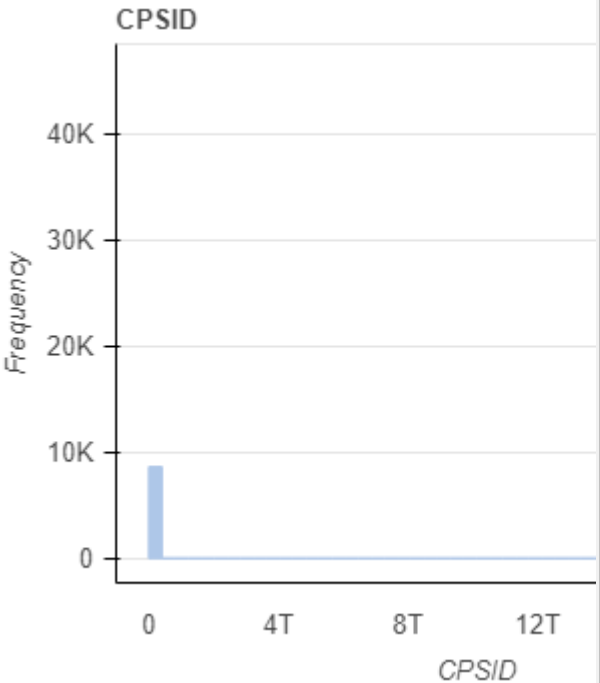
Mean	4.9545
Minimum	1
Maximum	12
Zeros	0
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%



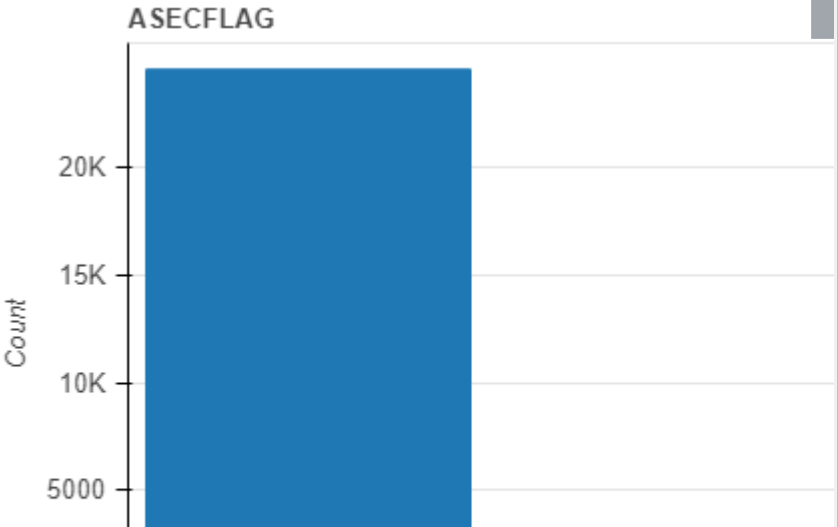
Approximate distinct count	29375	Mean	2969.6539
Approximate unique (%)	97.4%	Minimum	212.2263
Missing	24577	Maximum	13173.7325
Missing (%)	44.9%	Zeros	0
finite	0	Zeros (%)	0.0%
finite (%)	0.0%	Negatives	0
Memory Size	471.2 KB	Negatives (%)	0.0%



Approximate distinct count	43204	Mean	$1.7002 \times 10^{13}$
Approximate unique (%)	78.9%	Minimum	0
Missing	0	Maximum	$2.022 \times 10^{13}$
Missing (%)	0.0%	Zeros	8617
finite	0	Zeros (%)	15.7%
finite (%)	0.0%	Negatives	0
Memory Size	855.3 KB	Negatives (%)	0.0%



ASECFLAG categorical	Approximate Distinct Count	2
	Approximate Unique (%)	0.0%
	Missing	28042
	Missing (%)	51.2%
	Memory Size	1.7 MB

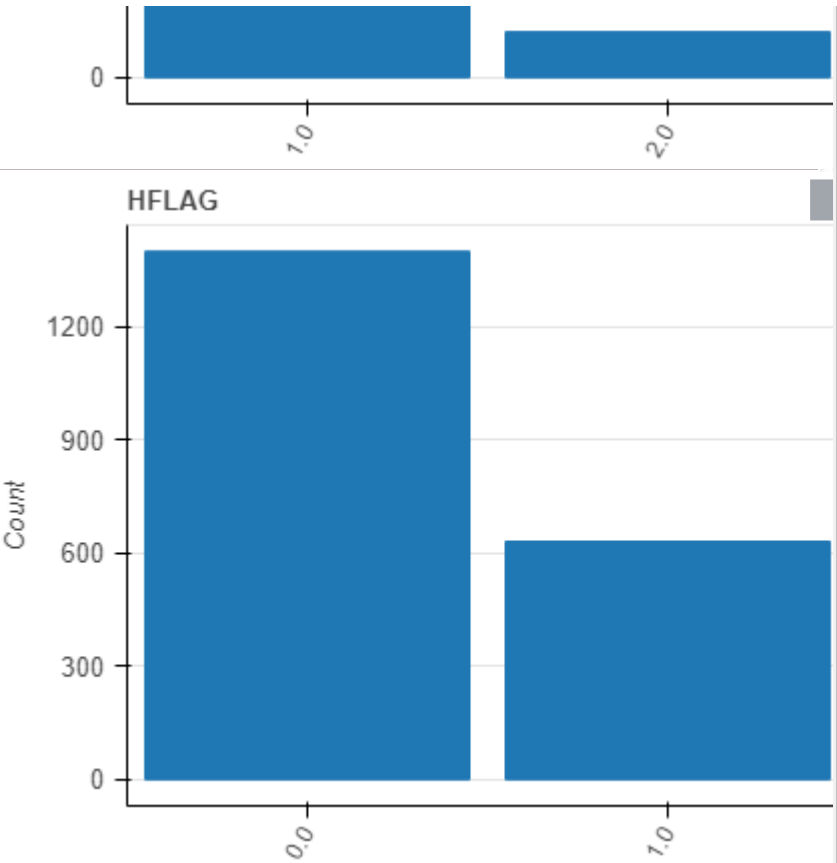




HFLAG  
categorical

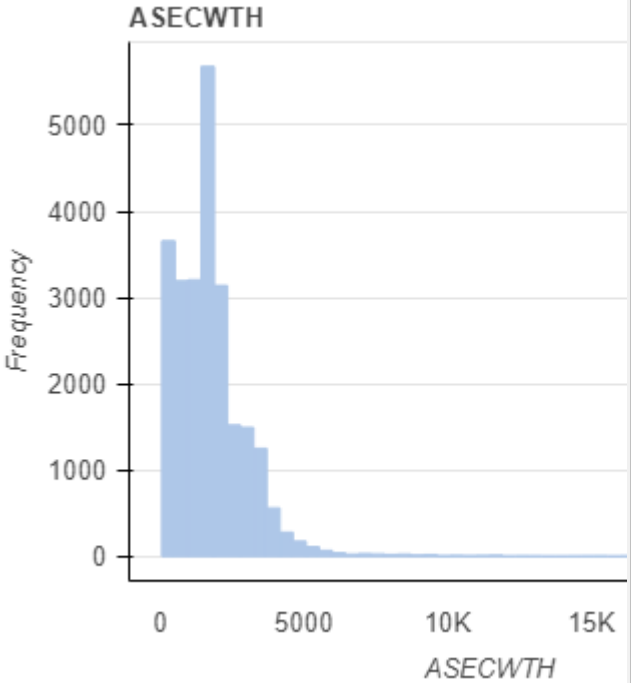
Show Details

Approximate Distinct Count	2
Approximate Unique (%)	0.1%
Missing	52709
Missing (%)	96.3%
Memory Size	134.7 KB



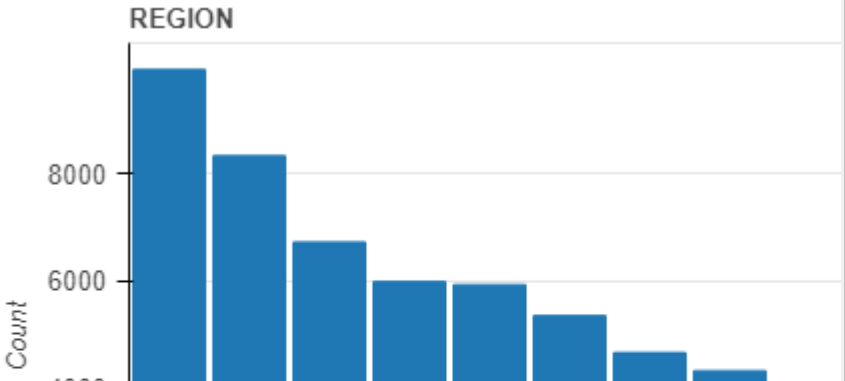
Approximate Distinct Count	22998
Approximate Unique (%)	93.6%
Missing	30160
Missing (%)	55.1%
nfinite	0
nfinite (%)	0.0%
Memory Size	384.0 KB

Mean	1763.6123
Minimum	52.51
Maximum	22869.35
Zeros	0
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%



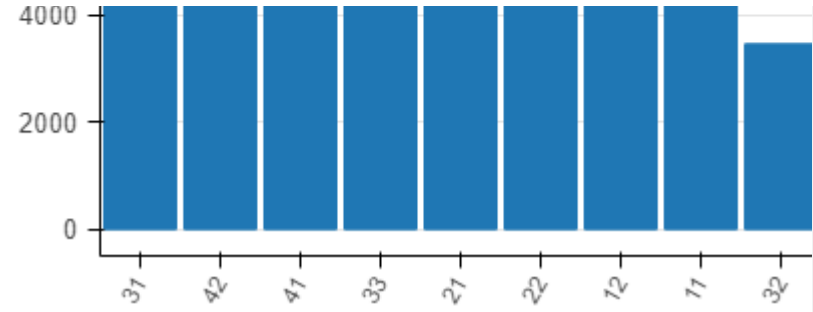
REGION  
categorical

Approximate Distinct Count	9
Approximate Unique (%)	0.0%
Missing	0

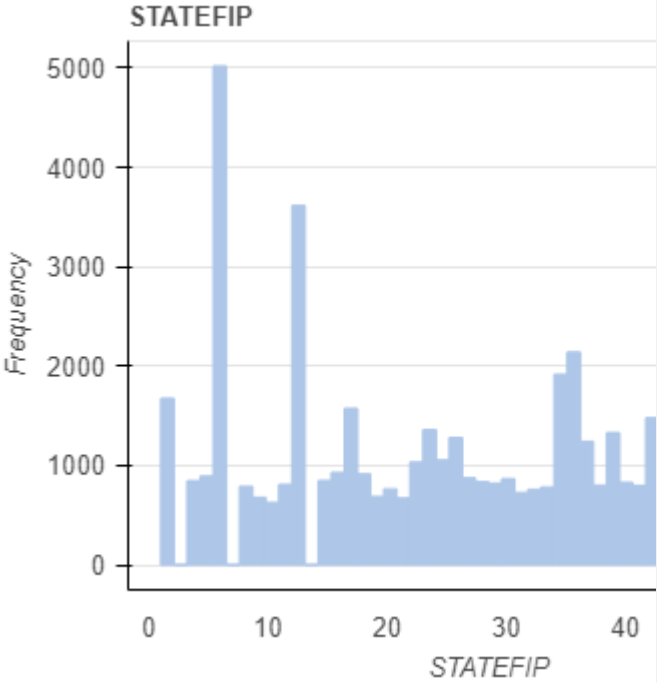


Show Details

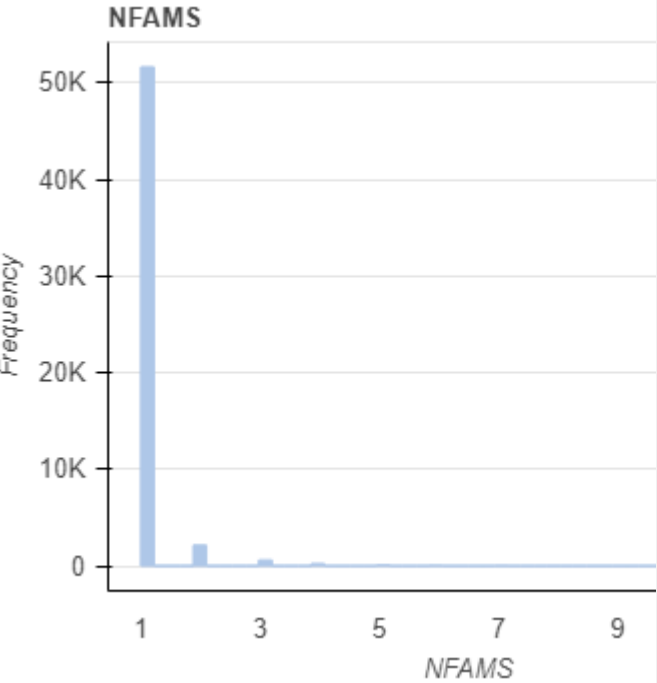
Missing (%)	0.0%
Memory Size	3.5 MB



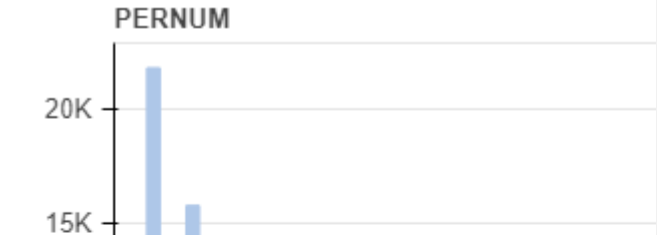
Approximate Distinct Count	51	Mean	27.9278
Approximate Unique (%)	0.1%	Minimum	1
Missing	0	Maximum	56
Missing (%)	0.0%	Zeros	0
Infinite	0	Zeros (%)	0.0%
Infinite (%)	0.0%	Negatives	0
Memory Size	855.3 KB	Negatives (%)	0.0%

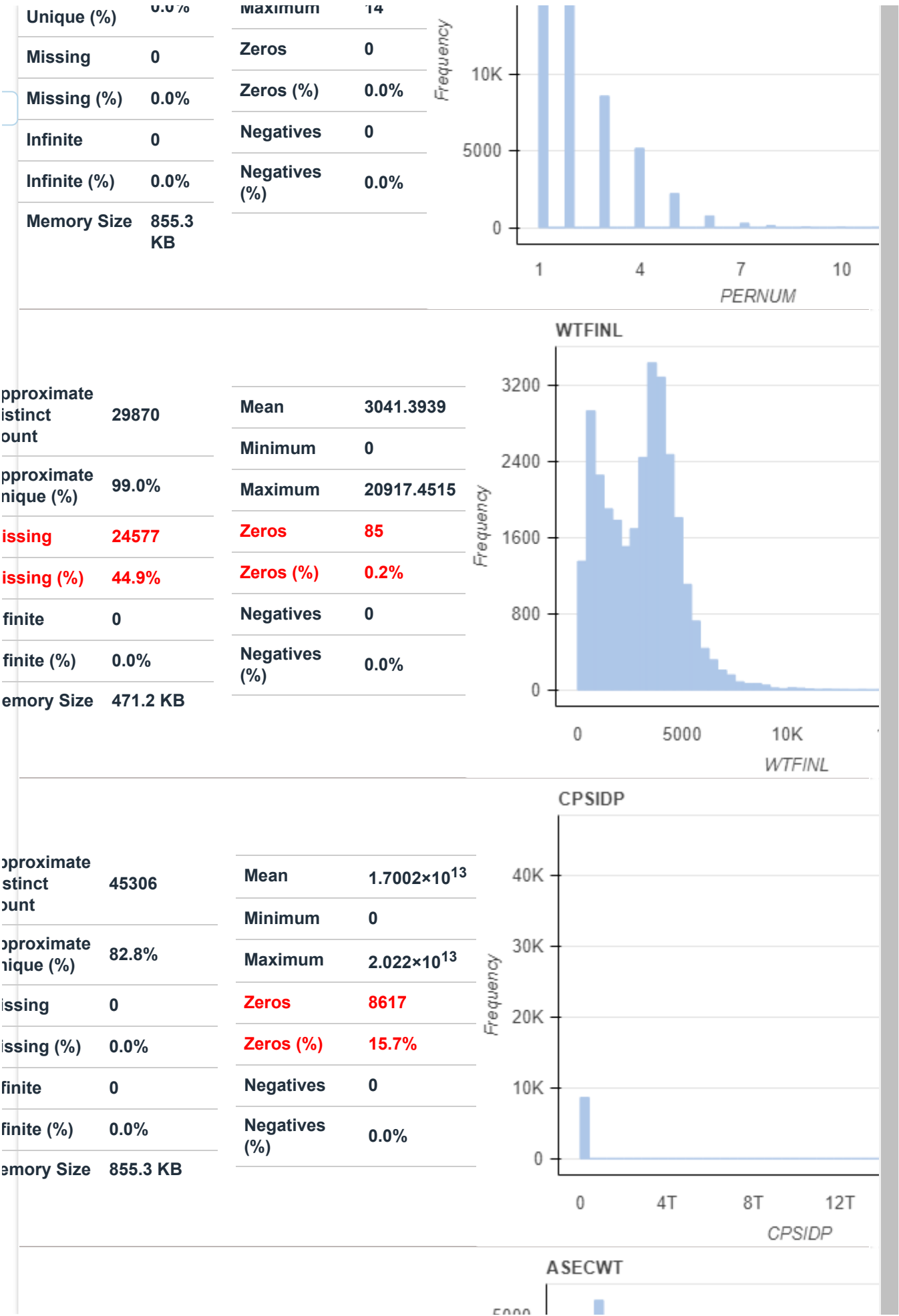


Approximate Distinct Count	11	Mean	1.0848
Approximate Unique (%)	0.0%	Minimum	1
Missing	0	Maximum	12
Missing (%)	0.0%	Zeros	0
Infinite	0	Zeros (%)	0.0%
Infinite (%)	0.0%	Negatives	0
Memory Size	855.3 KB	Negatives (%)	0.0%



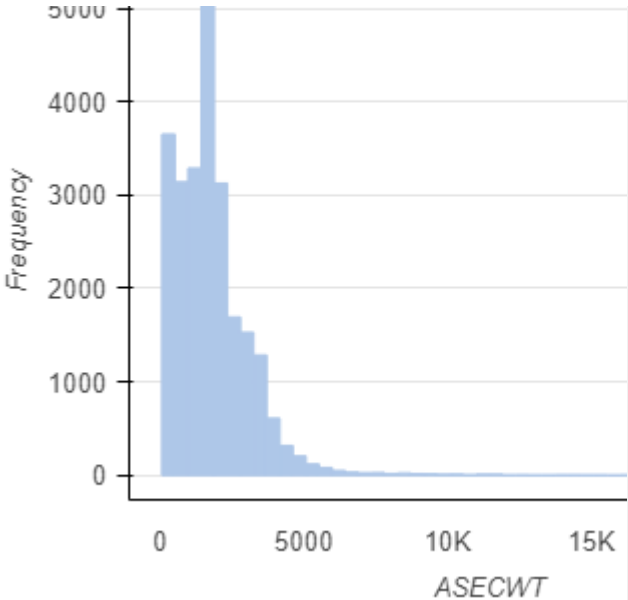
Approximate Distinct Count	14	Mean	2.1785
Approximate Unique (%)	0.0%	Minimum	1
Missing	0	Maximum	44
Missing (%)	0.0%	Zeros	0
Infinite	0	Zeros (%)	0.0%
Infinite (%)	0.0%	Negatives	0
Memory Size	855.3 KB	Negatives (%)	0.0%





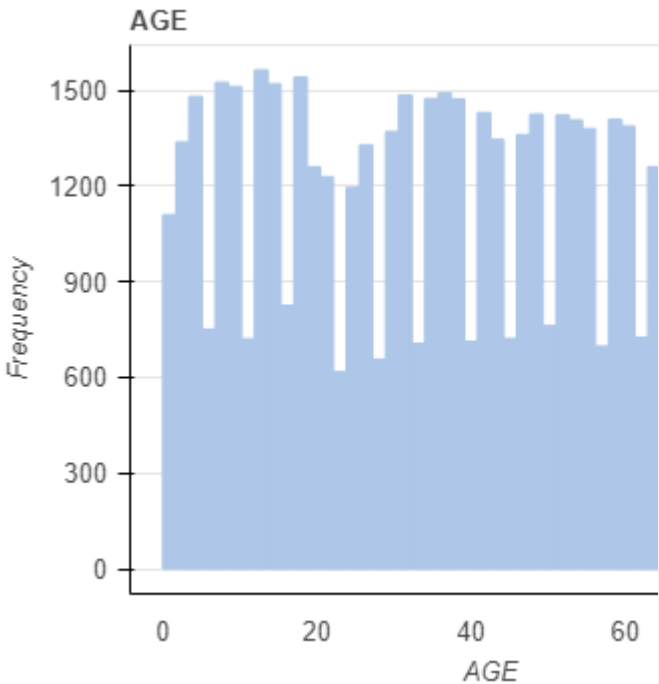
Approximate Distinct Count	23483
Approximate Unique (%)	95.5%
Missing	30160
Missing (%)	55.1%
nfinite	0
nfinite (%)	0.0%
Memory Size	384.0 KB

Mean	1802.5003
Minimum	54.58
Maximum	22869.35
Zeros	0
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%

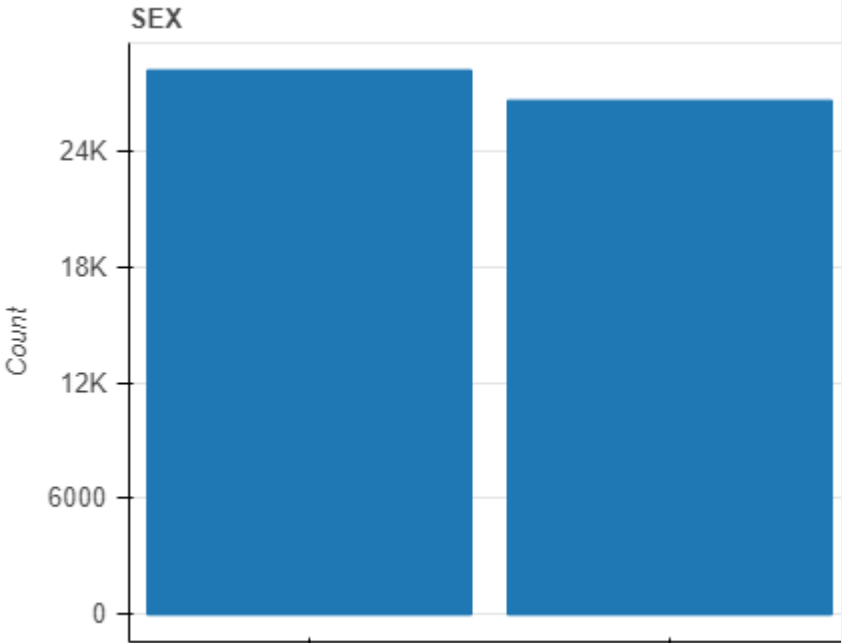


Approximate Distinct Count	82
Approximate Unique (%)	0.1%
Missing	0
Missing (%)	0.0%
Infinite	0
Infinite (%)	0.0%
Memory Size	855.3 KB

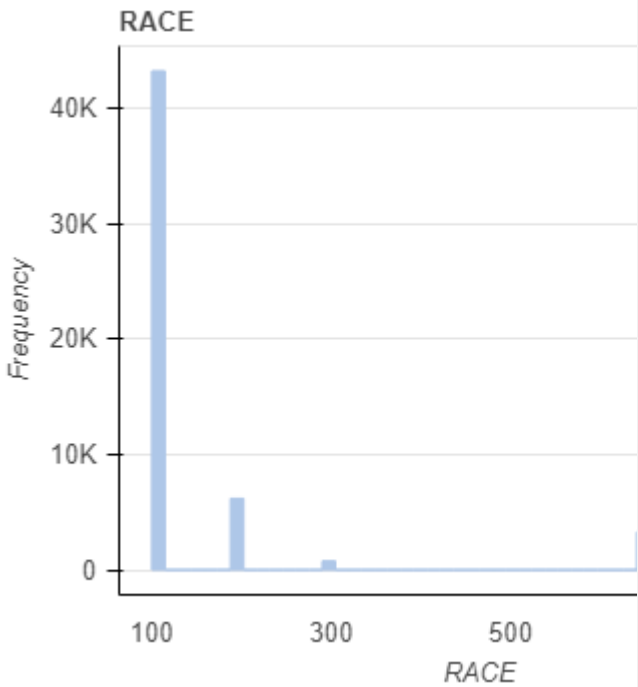
Mean	38.8724
Minimum	0
Maximum	85
Zeros	503
Zeros (%)	0.9%
Negatives	0
Negatives (%)	0.0%



<b>SEX</b> categorical <div>Show Details</div>	Approximate Distinct Count	2
	Approximate Unique (%)	0.0%
	Missing	0
	Missing (%)	0.0%
	Memory Size	3.4 MB

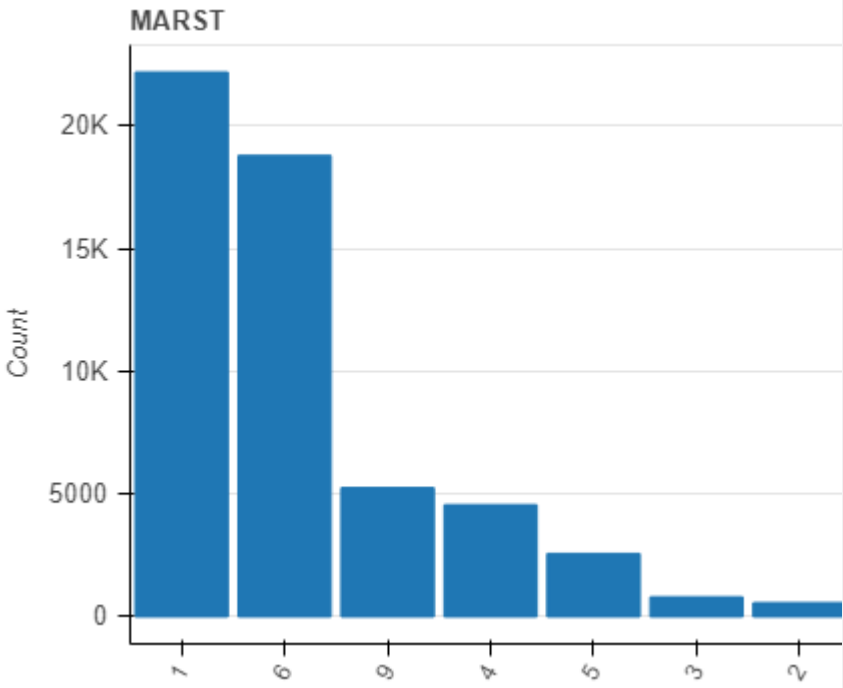


Approximate Distinct Count	24	Mean	163.7212
Approximate Unique (%)	0.0%	Minimum	100
Missing	0	Maximum	830
Missing (%)	0.0%	Zeros	0
Infinite	0	Zeros (%)	0.0%
Infinite (%)	0.0%	Negatives	0
Memory Size	855.3 KB	Negatives (%)	0.0%

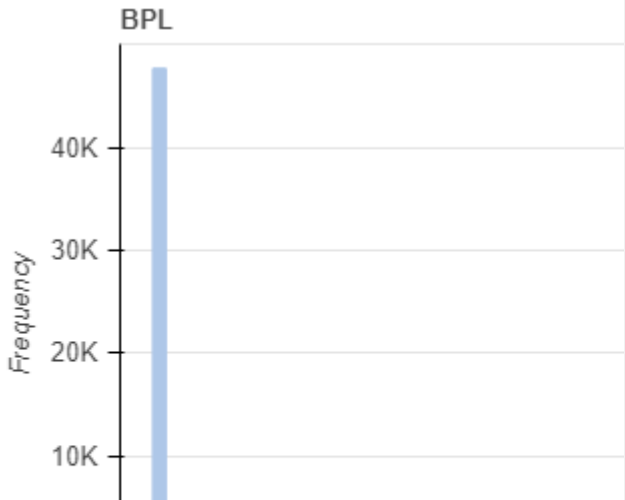


MARST categorical	Approximate Distinct Count	7
	Approximate Unique (%)	0.0%
	Missing	0
	Missing (%)	0.0%
	Memory Size	3.4 MB

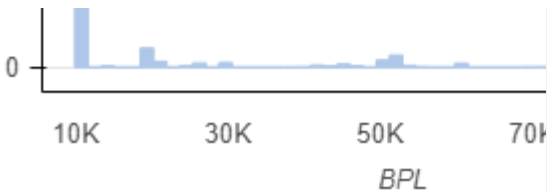
Show Details



Approximate Distinct Count	161	Mean	13279.508
Approximate Unique (%)	0.3%	Minimum	9900
Missing	0	Maximum	96000
Missing (%)	0.0%	Zeros	0
Infinite	0	Zeros (%)	0.0%
		Negatives	0



Infinite (%)	0.0%	negatives (%)	0.0%
Memory Size	855.3 KB		



EMPSTAT

categorical

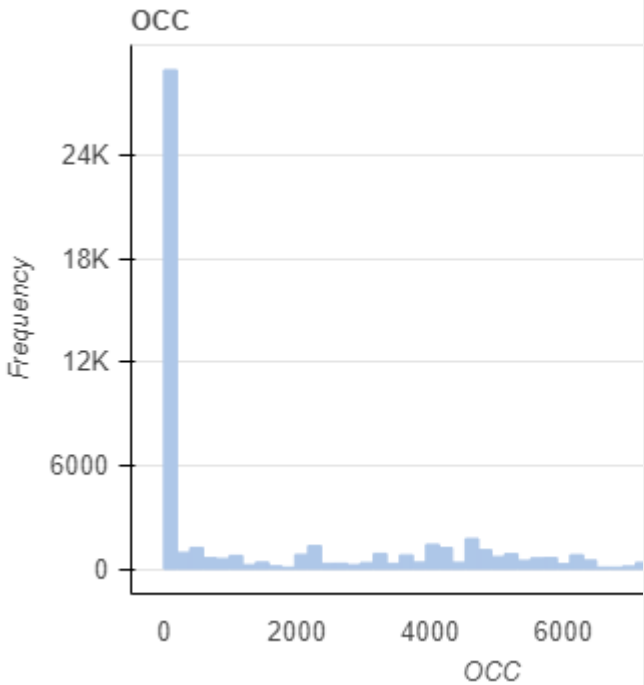
Show Details

Approximate Distinct Count	9
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	3.5 MB

EMPSTAT

A histogram showing the distribution of EMPSTAT values. The x-axis represents categories: 10, 0, 36, 34, 32, 27, 12, 7, 22. The y-axis is labeled 'Count' and ranges from 0 to 20K. The distribution is highly right-skewed, with the highest frequency at category 10 (over 20K) and a long tail extending towards category 22.

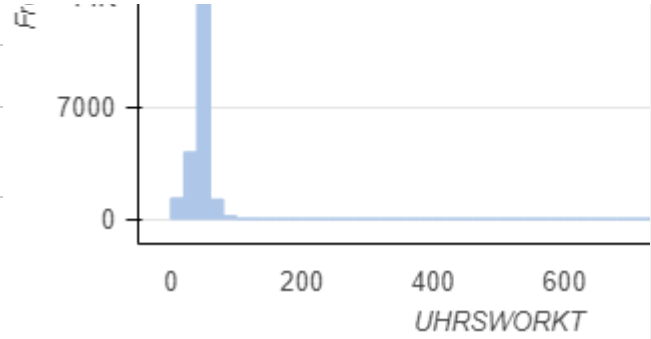
Approximate Distinct Count	654	Mean	2021.451
Approximate Unique (%)	1.2%	Minimum	0
Missing	0	Maximum	9840
Missing (%)	0.0%	Zeros	27716
Infinite	0	Zeros (%)	50.6%
Infinite (%)	0.0%	Negatives	0
Memory Size	855.3 KB	Negatives (%)	0.0%



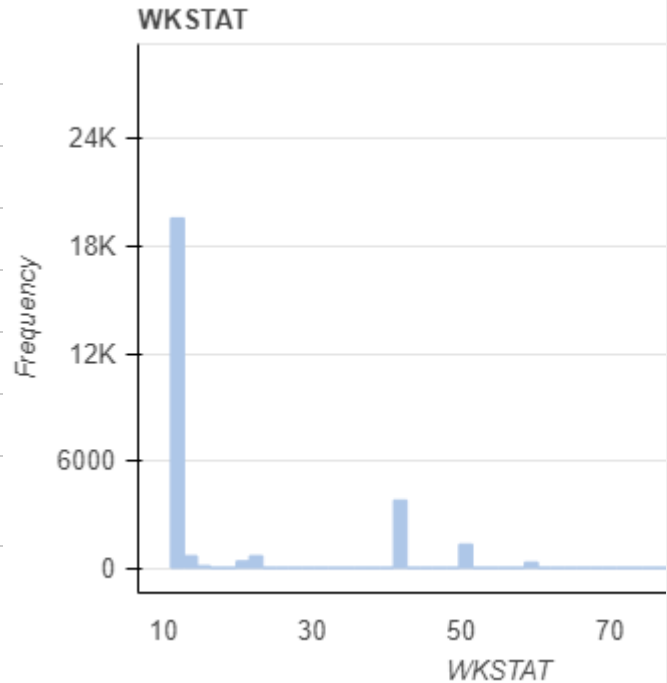
Approximate Distinct Count	100	Mean	590.1611
Approximate Unique (%)	0.2%	Minimum	0
Missing	0	Maximum	999
		Zeros	18



Missing (%)	0.0%	Zeros (%)	0.0%
Infinite	0	Negatives	0
Infinite (%)	0.0%	Negatives (%)	0.0%
Memory Size	855.3 KB		

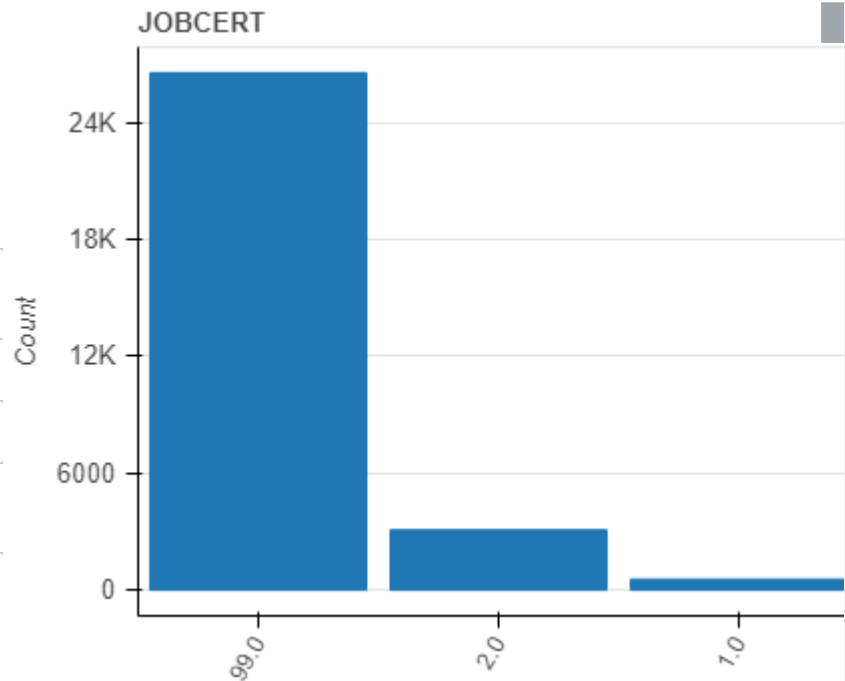


Approximate Distinct Count	12	Mean	59.4543
Approximate Unique (%)	0.0%	Minimum	11
Missing	0	Maximum	99
Missing (%)	0.0%	Zeros	0
Infinite	0	Zeros (%)	0.0%
Infinite (%)	0.0%	Negatives	0
Memory Size	855.3 KB	Negatives (%)	0.0%

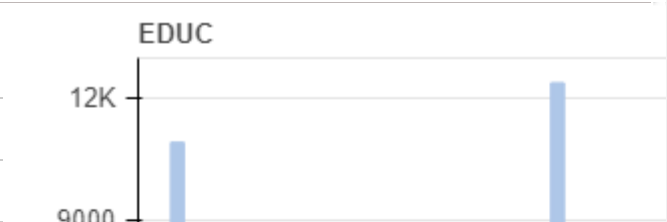


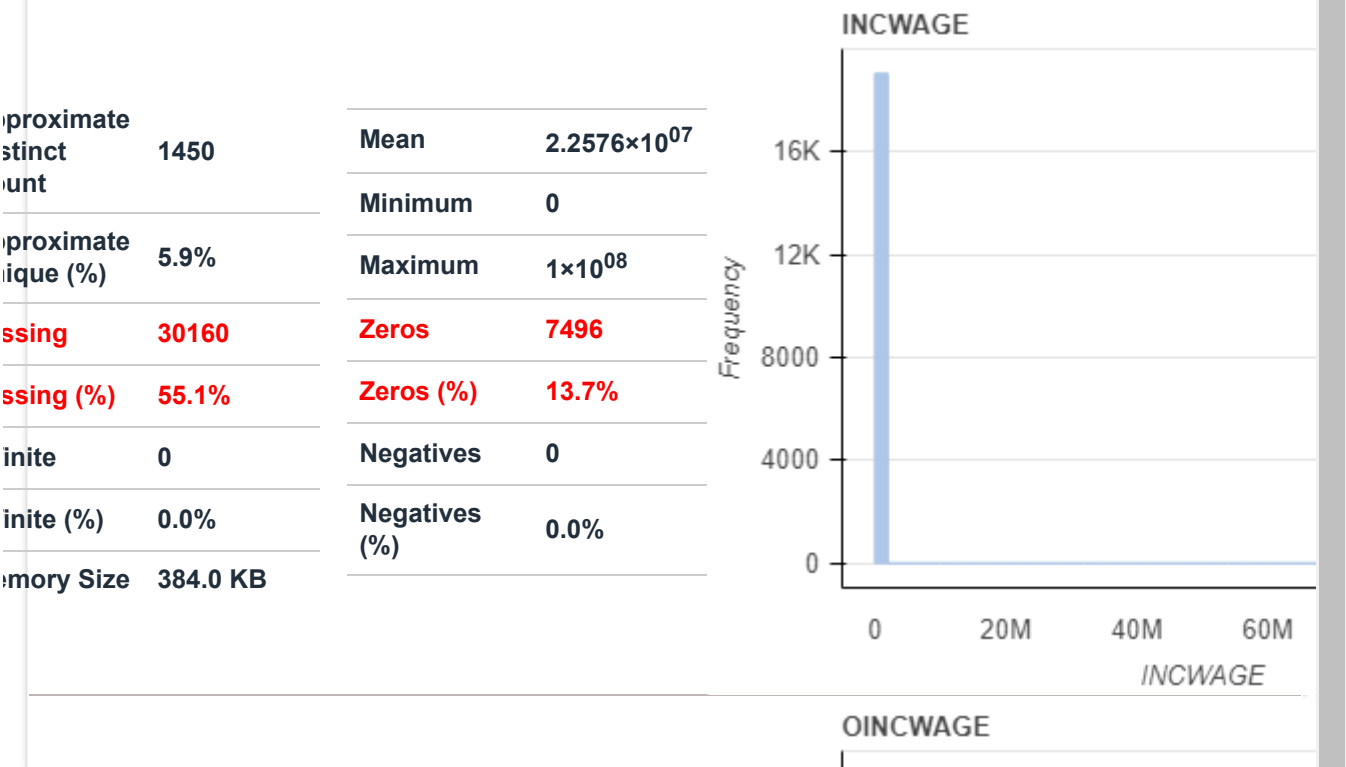
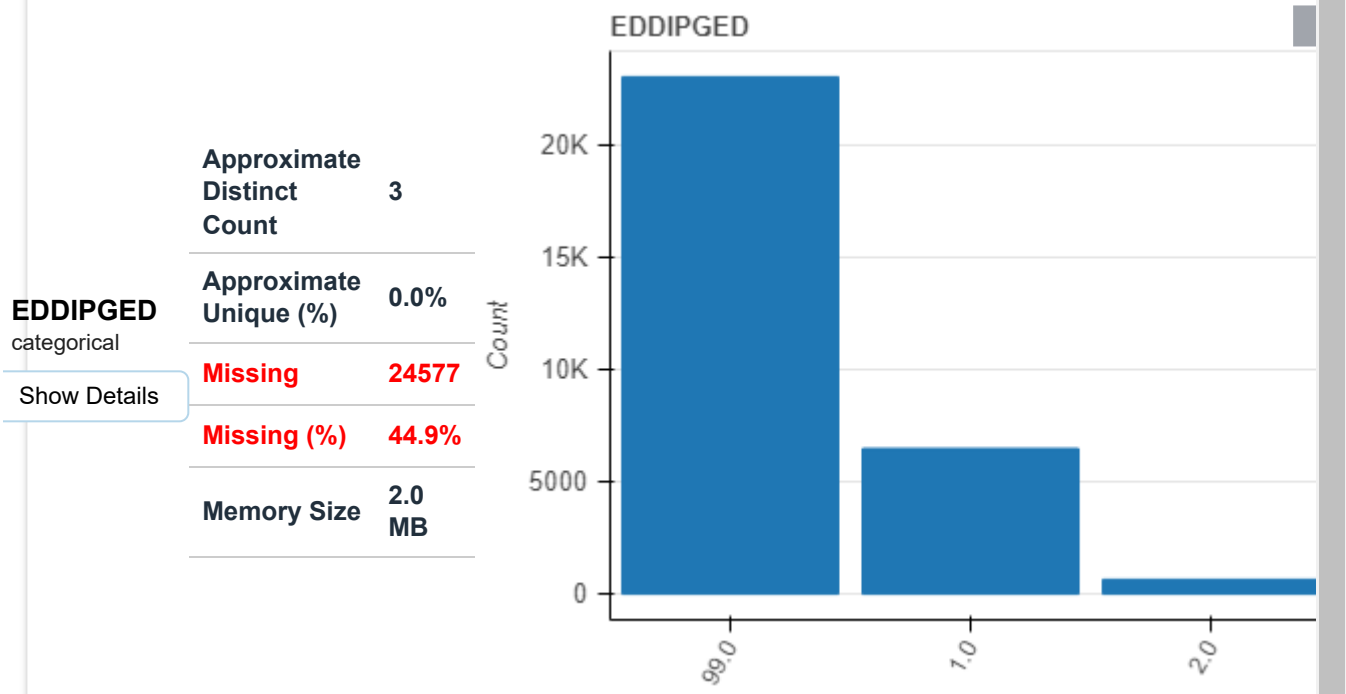
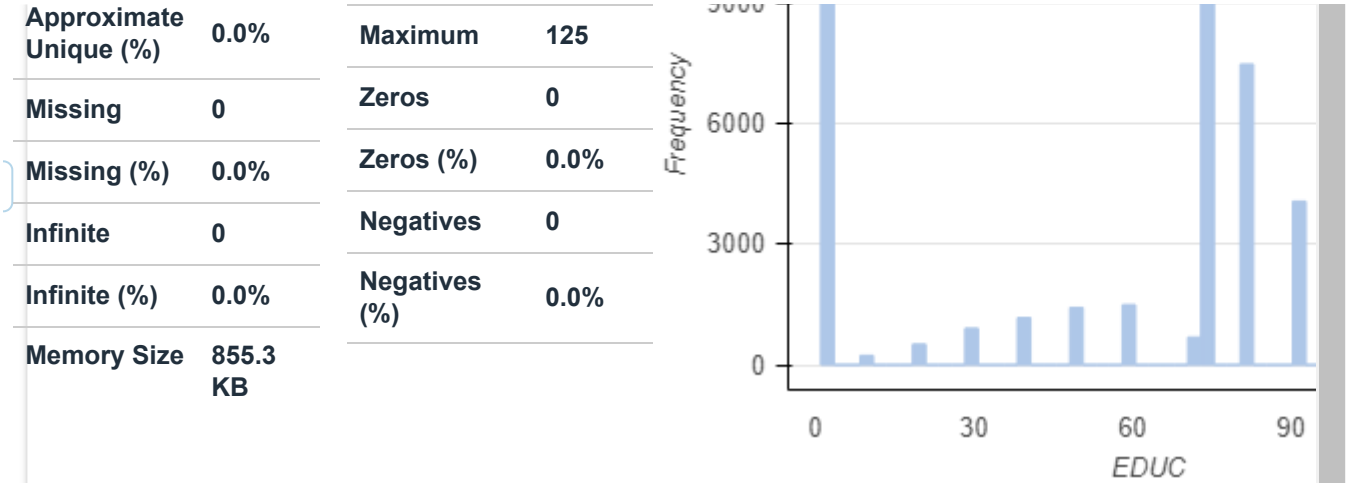
JOBCERT categorical	Approximate Distinct Count	3
	Approximate Unique (%)	0.0%
	Missing	24577
	Missing (%)	44.9%
	Memory Size	2.0 MB

Show Details



Approximate Distinct Count	17	Mean	68.4491
		Minimum	1







Approximate  
distinct  
count

278

Approximate  
unique (%)

1.1%

Missing

30160

Missing (%)

55.1%

inite

0

inite (%)

0.0%

emory Size

384.0 KB

Mean

 $2.2554 \times 10^7$ 

Minimum

0

Maximum

 $1 \times 10^8$ 

Zeros

17838

Zeros (%)

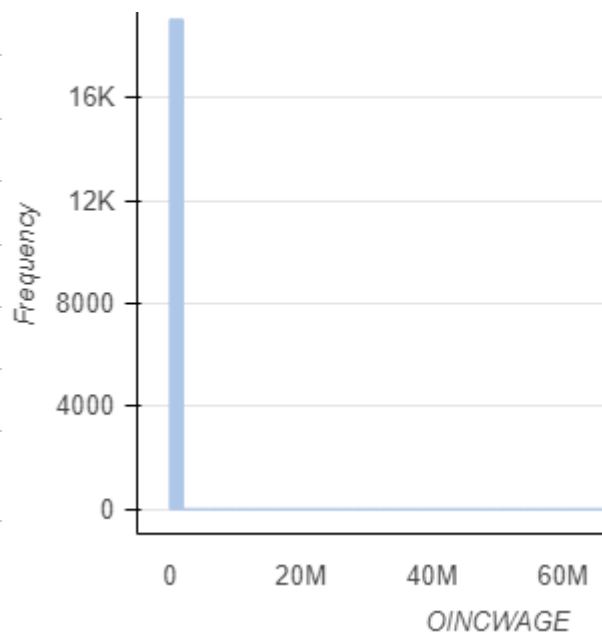
32.6%

Negatives

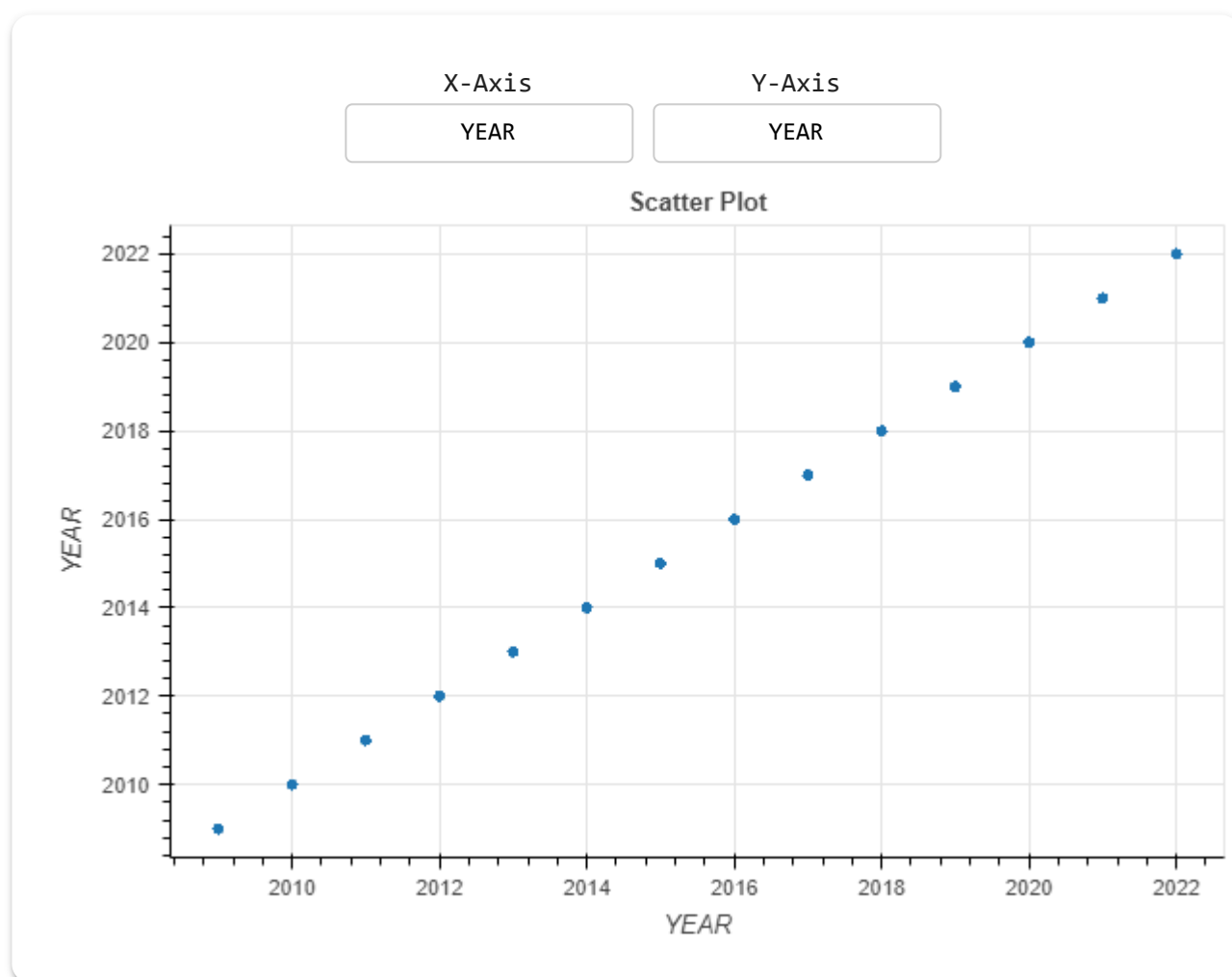
0

Negatives  
(%)

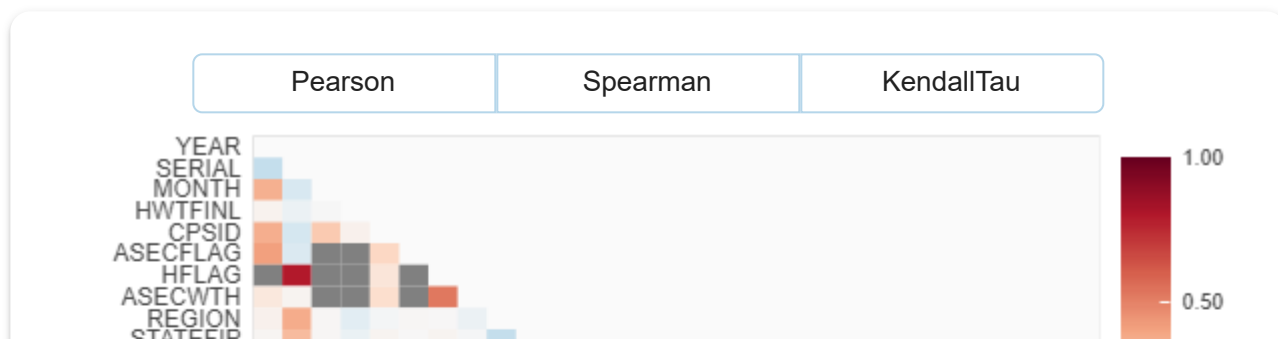
0.0%



## Interactions



# Correlations



## ▼ Cleaning the data

```
train.dropna()
```

```
YEAR  SERIAL  MONTH  HWTFINL  CPSID  ASECFLAG  HFLAG  ASECWTH  REGION  STATEFIP  ...
0 rows x 29 columns
```



## ▼ What about Categorical variables ? => Ordinal encoder

```
# Handling categorical attributes
from sklearn.preprocessing import OrdinalEncoder
ordinal_encoder = OrdinalEncoder()
train['EDDIPGED'] = ordinal_encoder.fit_transform(train[['EDDIPGED']])
train['JOBCERT'] = ordinal_encoder.fit_transform(train[['JOBCERT']])
train['EMPSTAT'] = ordinal_encoder.fit_transform(train[['EMPSTAT']])
train['MARST'] = ordinal_encoder.fit_transform(train[['MARST']])
train['SEX'] = ordinal_encoder.fit_transform(train[['SEX']])
train['REGION'] = ordinal_encoder.fit_transform(train[['REGION']])
train['HFLAG'] = ordinal_encoder.fit_transform(train[['HFLAG']])
train['ASECFLAG'] = ordinal_encoder.fit_transform(train[['ASECFLAG']])
```

```
df=train
```

```
#Dropping non correlated columns to INCWAGE
l=['YEAR', 'SERIAL', 'REGION', 'STATEFIP', 'NFAMS', 'SEX', 'RACE', 'BPL', 'HFLAG',]
df.drop(l, inplace=True, axis=1)
```

```
#Removing NAN values
```

```
for i in df.columns:
    vals = pd.to_numeric(df[i], errors='coerce')
    df[i] = vals.fillna(vals.mean())
```

df

	MONTH	HWTFINL	CPSID	ASECFLAG	ASECWTH	PERNUM	WTF
0	3	2969.653939	0	0.000000	1671.320000	1	3041.393
1	6	1930.450500	20200504991400	0.079341	1763.612314	3	1718.642
2	3	2969.653939	0	0.000000	433.890000	2	3041.393
3	3	2969.653939	20091201475800	0.000000	2996.700000	1	3041.393
4	3	2969.653939	20170102597500	0.000000	1719.160000	3	3041.393
...	...	...	...	...	...	...	...
54732	10	766.129300	20191004211300	0.079341	1763.612314	1	766.129
54733	3	2969.653939	20100300901100	0.000000	1477.030000	1	3041.393
54734	11	873.029400	20201006551800	0.079341	1763.612314	3	1468.447
54735	12	4327.645400	20201005723900	0.079341	1763.612314	2	4464.994
54736	3	2969.653939	0	0.000000	570.480000	2	3041.393

54737 rows × 20 columns



```
df = df[df.get("INCWAGE") != 0]

vals = pd.to_numeric(df['INCWAGE'], errors='coerce')
vals
```

0	1.000000e+05
1	2.257584e+07
5	1.000000e+08
6	2.257584e+07
7	2.257584e+07
...	...
54732	2.257584e+07
54733	3.600000e+03
54734	2.257584e+07
54735	2.257584e+07
54736	1.000000e+08
Name: INCWAGE, Length: 47241, dtype: float64	

- ▼ The target variable is very unbalanced so you need to figure out how to fight overfitting in this problem
- ▼ For now we will use only the numerical features

```
df.columns
```

```
Index(['MONTH', 'HWTFINL', 'CPSID', 'ASECFLAG', 'ASECWTH', 'PERNUM', 'WTFINL',
      'CPSIDP', 'ASECWT', 'AGE', 'MARST', 'EMPSTAT', 'OCC', 'UHRSWORKT',
      'WKSTAT', 'JOBCERT', 'EDUC', 'EDDIPGED', 'INCWAGE', 'OINCWAGE'],
      dtype='object')
```

```
main_cols=['MONTH', 'HWTFINL', 'CPSID', 'ASECFLAG', 'ASECWTH', 'PERNUM', 'WTFINL',
          'ASECWT', 'AGE', 'MARST', 'EMPSTAT', 'OCC', 'UHRSWORKT', 'WKSTAT',
          'JOBCERT', 'EDUC', 'EDDIPGED']
```

```
X=df[main_cols]
y=df.INCWAGE
```

```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.33,random_state=42)
```

```
from sklearn.ensemble import RandomForestRegressor
clf=RandomForestRegressor(max_depth=100, random_state=101,
                          max_features=None, min_samples_leaf=15)
clf.fit(X_train,y_train)
```

```
RandomForestRegressor(max_depth=100, max_features=None, min_samples_leaf=15,
                      random_state=101)
```

```
y_pred=clf.predict(X_test)
print(y_pred)
```

```
[4.54636958e+04 2.08239721e+04 2.25758421e+07 ... 9.99999990e+07
 2.25758421e+07 9.99999990e+07]
```

```
print(clf.score(X_train, y_train))
print(clf.score(X_test, y_test))
```

```
0.9999993441476379
0.999999255366242
```

---

✓ 0s completed at 9:35 PM

● ✕