UCI ML Repo - credit card defaults

Preprocessing

Platform: Python 3, colab.research.google.com

```
import datetime
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from google.colab import drive
```

```
sns.set(style='whitegrid', context='notebook')
```

Load data

```
drive.mount('/content/gdrive', force_remount=False)
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/content/gdrive"
```

```
data = pd.read_csv("/content/gdrive/My Drive/Colab Notebooks/uci-credit-card-defaults/data/defaults.csv", header=
data.shape
```

```
(30000, 25)
```

```
data.head(5)
```

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5	BILL_A
0	1	20000	2	2	1	24	2	2	-1	-1	...	0	0	
1	2	120000	2	2	2	26	-1	2	0	0	...	3272	3455	3
2	3	90000	2	2	2	34	0	0	0	0	...	14331	14948	15
3	4	50000	2	2	1	37	0	0	0	0	...	28314	28959	29
4	5	50000	1	2	1	57	-1	0	-1	0	...	20940	19146	19

```
data.tail(5)
```

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5
29995	29996	220000	1	3	1	39	0	0	0	0	...	88004	31237
29996	29997	150000	1	3	2	43	-1	-1	-1	-1	...	8979	5190
29997	29998	30000	1	2	2	37	4	3	2	-1	...	20878	20582
29998	29999	80000	1	3	1	41	1	-1	0	0	...	52774	11855
29999	30000	50000	1	2	1	46	0	0	0	0	...	36535	32428

5 rows × 25 columns

Exploration

```
data.dtypes
```

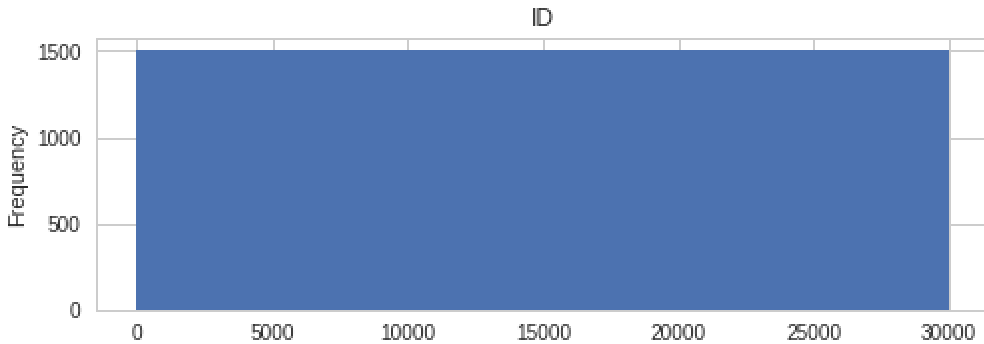
```
ID                            int64
LIMIT_BAL                     int64
SEX                           int64
EDUCATION                     int64
MARRIAGE                      int64
AGE                           int64
PAY_0                         int64
PAY_2                         int64
PAY_3                         int64
PAY_4                         int64
PAY_5                         int64
PAY_6                         int64
BILL_AMT1                     int64
BILL_AMT2                     int64
BILL_AMT3                     int64
BILL_AMT4                     int64
BILL_AMT5                     int64
BILL_AMT6                     int64
PAY_AMT1                      int64
PAY_AMT2                      int64
PAY_AMT3                      int64
PAY_AMT4                      int64
PAY_AMT5                      int64
PAY_AMT6                      int64
default payment next month    int64
```

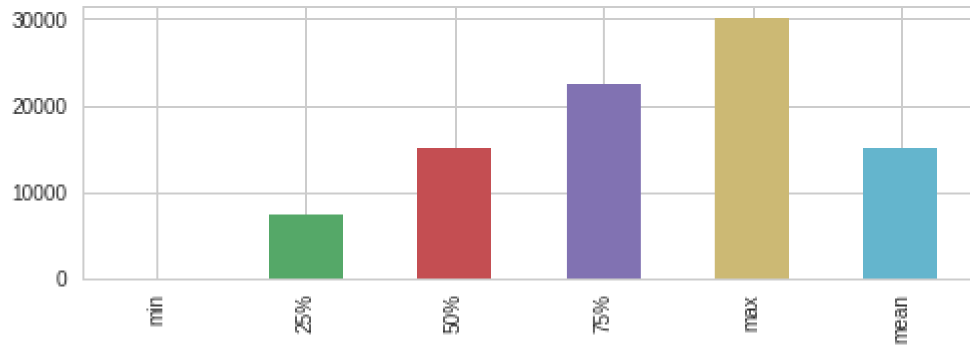
```
data.describe()
```

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000

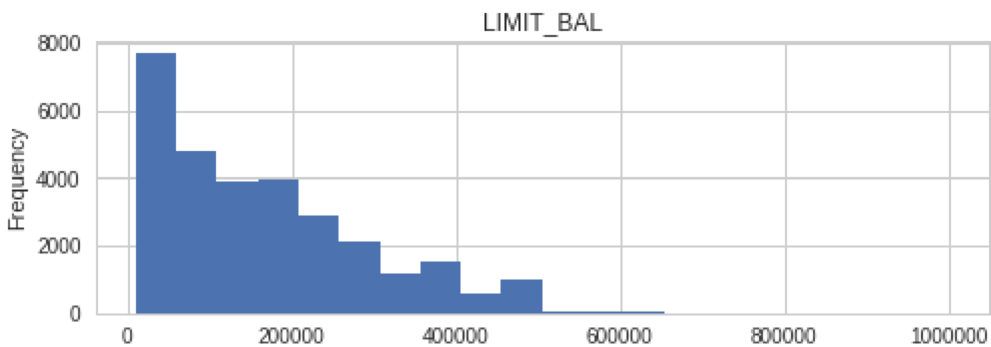
```
# explore distribution of numerical features
def chart_distribution(df: pd.DataFrame):
    column_distributions = df.describe()
    idx = 0
    for i in column_distributions:
        fig = plt.figure()
        ax11 = fig.add_subplot(211)
        ax21 = fig.add_subplot(212)
        df.loc[:,i].plot(kind="hist", bins=20, title=i, ax=ax11)
        column_distributions.loc[["min", "25%", "50%", "75%", "max", "mean"], i].plot(
            kind="bar", ax=ax21)
        print(idx, i)
        plt.show()
        idx += 1
chart_distribution(data)
```

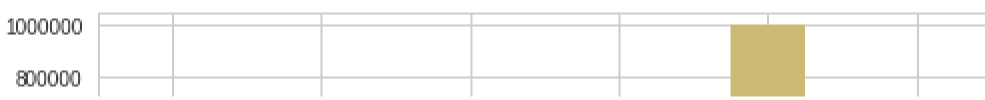
0 ID





1 LIMIT_BAL






```python
# explore distribution of categorical features
def chart_categorical(df: pd.DataFrame):
    idx = 0
    for col in df:
        if df[col].dtype == "object":
            df[col].value_counts().plot(kind="bar")
            print(idx, col)
```

```
            plt.show()
            idx += 1
chart_categorical(data)
```

Potential data errors to review:

- education should only have classes 1-4, dataset includes classes 0-6
- marriage should only have classes 1-3, dataset includes classes 0-3
- PAY_1 - PAY_6: represent payment delay in months. -1 is duly paid. now includes -2 and 0 as well
- BILL_AMT1 - BILL_AMT6: includes negative numbers and outliers
- PAY_AMT1 - PAY_AMT6: includes outliers

```
# rename columns
data_clean = data.copy(deep=True)
cols = list(data_clean.columns)
cols = [i.lower() for i in cols]
cols[-1] = "default"
data_clean.columns = cols
data_clean.columns
```

```
Index(['id', 'limit_bal', 'sex', 'education', 'marriage', 'age', 'pay_0',
       'pay_2', 'pay_3', 'pay_4', 'pay_5', 'pay_6', 'bill_amt1', 'bill_amt2',
       'bill_amt3', 'bill_amt4', 'bill_amt5', 'bill_amt6', 'pay_amt1',
       'pay_amt2', 'pay_amt3', 'pay_amt4', 'pay_amt5', 'pay_amt6', 'default'],
      dtype='object')
```

```
# fix education classes
data_clean.loc[data_clean["education"]==0, "education"] = 4
data_clean.loc[data_clean["education"]==5, "education"] = 4
data_clean.loc[data_clean["education"]==6, "education"] = 4
data_clean.loc[:, "education"].unique()
```

```
array([2, 1, 3, 4])
```

```
# fix marriage classes
data_clean.loc[data_clean["marriage"]==0, "marriage"] = 3
data_clean.loc[:, "marriage"].unique()
```

```
array([1, 2, 3])
```

Duplicates

```
# verify no duplicates exist
data_clean.loc[data_clean.duplicated()==True, ]
```

id	limit_bal	sex	education	marriage	age	pay_0	pay_2	pay_3	pay_4	...	bill_amt4	bill_amt5	bill_am

0 rows × 25 columns

Missing data

```
def get_missing(df):
    exploration = pd.DataFrame(df.isnull().sum(),
                  columns=["no_missing"])
    exploration = exploration.merge(
        pd.DataFrame(df.dtypes, columns=["type"]),
        left_index=True, right_index=True)
    return exploration.loc[exploration["no_missing"]>0].sort_values(
        by="no_missing", ascending=False)
missing = get_missing(data_clean)
print("Column \t # missing values")
for i, row in missing.iterrows():
    print("{} \t {}".format(i, row["no_missing"]))
```

```
Column   # missing values
```

Outliers

```
bill_cols = ["bill_amt1", "bill_amt2", "bill_amt3", "bill_amt4", "bill_amt5", "bill_amt6"]
data_clean.loc[:,bill_cols].describe()
```

	bill_amt1	bill_amt2	bill_amt3	bill_amt4	bill_amt5	bill_amt6
count	30000.000000	30000.000000	3.000000e+04	30000.000000	30000.000000	30000.000000
mean	51223.330900	49179.075167	4.701315e+04	43262.948967	40311.400967	38871.760400
std	73635.860576	71173.768783	6.934939e+04	64332.856134	60797.155770	59554.107537
min	-165580.000000	-69777.000000	-1.572640e+05	-170000.000000	-81334.000000	-339603.000000
25%	3558.750000	2984.750000	2.666250e+03	2326.750000	1763.000000	1256.000000
50%	22381.500000	21200.000000	2.008850e+04	19052.000000	18104.500000	17071.000000
75%	67091.000000	64006.250000	6.016475e+04	54506.000000	50190.500000	49198.250000

```python
for i in bill_cols:
    bill_gt_600 = data_clean.loc[data_clean[i]>600000, [i]]
    print("col {} len {} where val > 600k. max {}".format(i, bill_gt_600.shape[0], bill_gt_600.max()[0]))
```

```
col bill_amt1 len 10 where val > 600k. max 964511
col bill_amt2 len 6 where val > 600k. max 983931
col bill_amt3 len 6 where val > 600k. max 1664089
col bill_amt4 len 4 where val > 600k. max 891586
col bill_amt5 len 2 where val > 600k. max 927171
col bill_amt6 len 2 where val > 600k. max 961664
```

All high bill data points assumed to be reasonable based on nearby values

```python
for i in bill_cols:
    bill_lt = data_clean.loc[data_clean[i]<-50000, [i]]
    print("col {} len {} where val < 50k. max {}".format(i, bill_lt.shape[0], bill_lt.min()[0]))
```

```
col bill_amt1 len 2 where val < 50k. max -165580
col bill_amt2 len 2 where val < 50k. max -69777
col bill_amt3 len 2 where val < 50k. max -157264
col bill_amt4 len 4 where val < 50k. max -170000
col bill_amt5 len 3 where val < 50k. max -81334
col bill_amt6 len 8 where val < 50k. max -339603
```

All negative bill data points assumed to be reasonable based on nearby values

```python
pay_cols = ["pay_amt1", "pay_amt2", "pay_amt3", "pay_amt4", "pay_amt5", "pay_amt6"]
data_clean.loc[:, pay_cols].describe()
```

	pay_amt1	pay_amt2	pay_amt3	pay_amt4	pay_amt5	pay_amt6
count	30000.000000	3.000000e+04	30000.00000	30000.000000	30000.000000	30000.000000
mean	5663.580500	5.921163e+03	5225.68150	4826.076867	4799.387633	5215.502567
std	16563.280354	2.304087e+04	17606.96147	15666.159744	15278.305679	17777.465775
min	0.000000	0.000000e+00	0.00000	0.000000	0.000000	0.000000
25%	1000.000000	8.330000e+02	390.00000	296.000000	252.500000	117.750000
50%	2100.000000	2.009000e+03	1800.00000	1500.000000	1500.000000	1500.000000
75%	5006.000000	5.000000e+03	4505.00000	4013.250000	4031.500000	4000.000000
max	873552.000000	1.684259e+06	896040.00000	621000.000000	426529.000000	528666.000000

```python
for i in pay_cols:
    pay_gt = data_clean.loc[data_clean[i]>400000, [i]]
    print("col {} len {} where val > 400k. max {}".format(i, pay_gt.shape[0], pay_gt.max()[0]))
```

```
col pay_amt1 len 5 where val > 400k. max 873552
col pay_amt2 len 7 where val > 400k. max 1684259
col pay_amt3 len 5 where val > 400k. max 896040
col pay_amt4 len 5 where val > 400k. max 621000
col pay_amt5 len 2 where val > 400k. max 426529
col pay_amt6 len 5 where val > 400k. max 528666
```

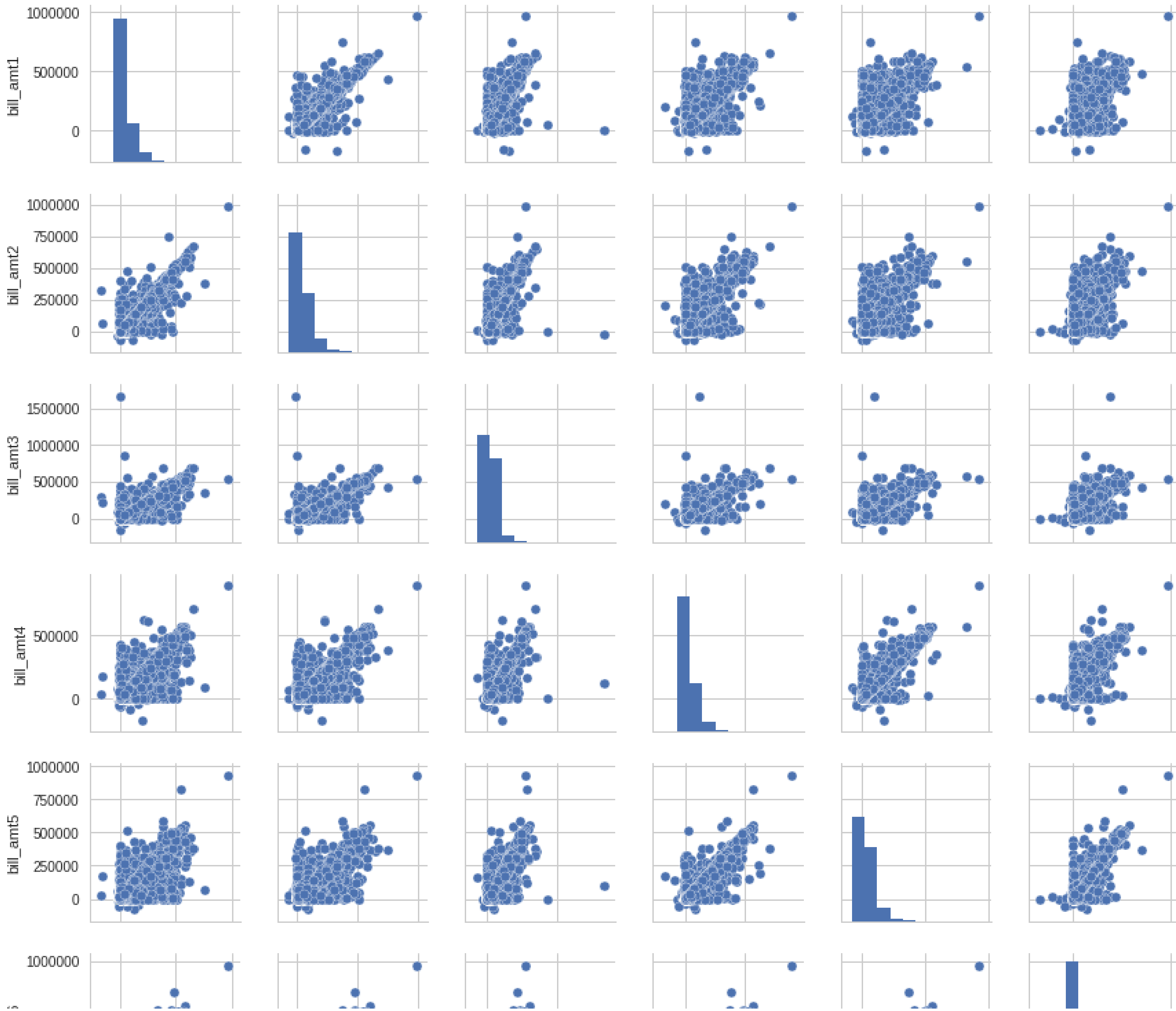
pay_amtx outliers appear valid due to other nearby datapoints

Correlated features

```python
# show correlation > threshold
def show_feature_correlation(df):
    df_corr = df.corr()
    high_correlations = pd.DataFrame(columns=["f1", "f2", "corr"])
    for i, row in df_corr.iterrows():
        for j in row.index:
            if i == j:
                continue
            high_correlations.loc[len(high_correlations), :] = [i, j, abs(df_corr.loc[i, j])]
    high_correlations = high_correlations.sort_values(by="corr", ascending=False)
    high_correlations = high_correlations.loc[high_correlations.loc[:, "corr"].duplicated(), :]
    return high_correlations
high_correlations = show_feature_correlation(data_clean)
print(high_correlations.head(10))
```

```
            f1         f2      corr
324  bill_amt2  bill_amt1  0.951484
400  bill_amt5  bill_amt6  0.946197
375  bill_amt4  bill_amt5  0.940134
349  bill_amt3  bill_amt2  0.928326
350  bill_amt3  bill_amt4  0.923969
423  bill_amt6  bill_amt4  0.900941
326  bill_amt2  bill_amt4  0.892482
301  bill_amt1  bill_amt3  0.892279
398  bill_amt5  bill_amt3   0.88391
372  bill_amt4  bill_amt1  0.860272
```

```python
show_corr = 0.90
correlation_cols = set()
for i, row in high_correlations.iterrows():
    if row["corr"] > show_corr:
        correlation_cols.add(row["f1"])
        correlation_cols.add(row["f2"])
correlation_cols
if len(correlation_cols) > 1:
    sns.pairplot(data_clean.loc[:, sorted(correlation_cols)], size=2)
    plt.show()
```



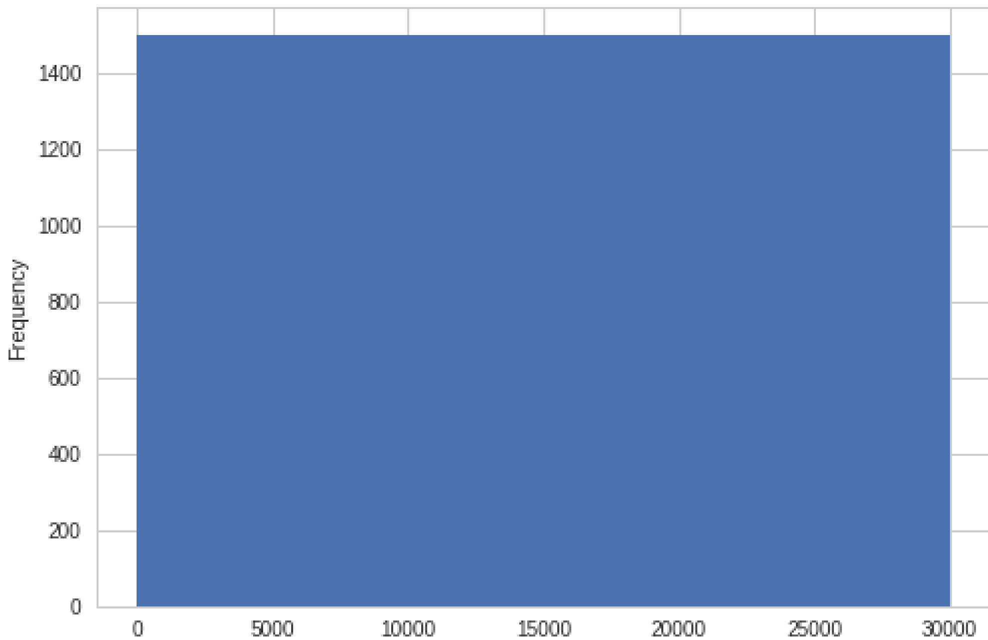
1000000
500000
0
bill_amt1
1000000
750000
500000
250000
0
bill_amt2
1500000
1000000
500000
0
bill_amt3
500000
0
bill_amt4
1000000
750000
500000
250000
0
bill_amt5
1000000

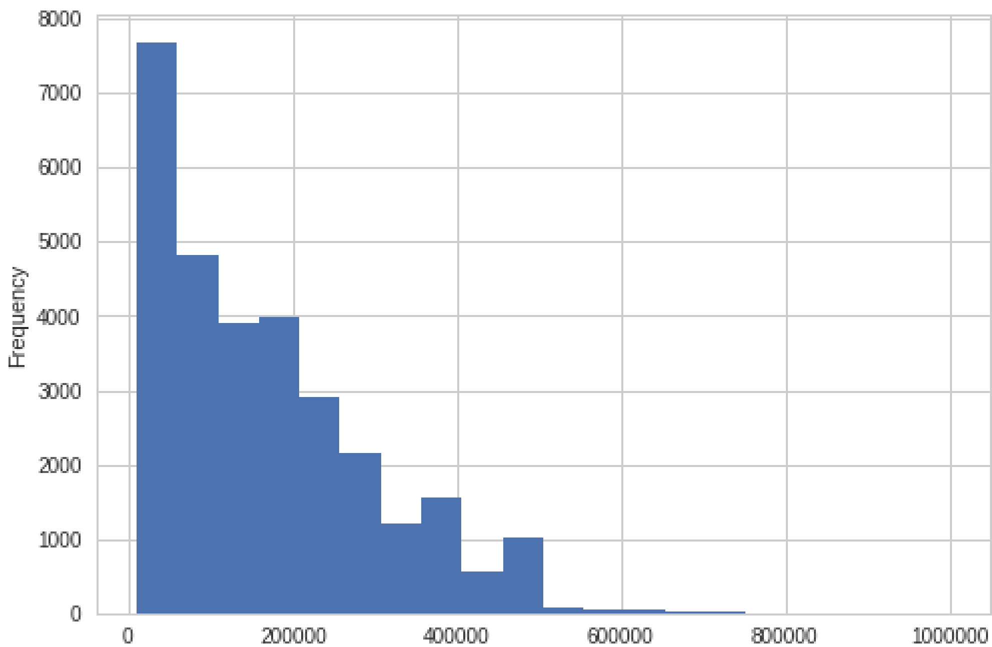

```python
# remove feature with correlation higher than 'remove_corr'
remove_corr = 0.99
for i in range(len(data_clean.columns)):
    for i, row in high_correlations.iterrows():
        if row["corr"] > remove_corr:
            data_clean = data_clean.drop(row["f2"], axis=1)
            high_correlations = show_feature_correlation(data_clean)
            break
print(high_correlations.head(10))
print(data_clean.columns)
```

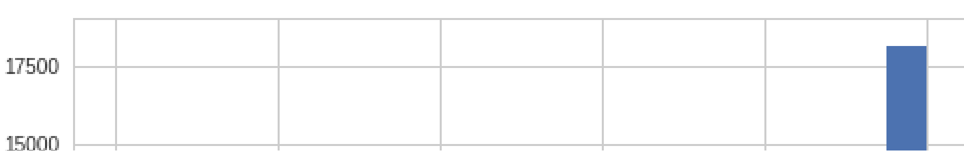
```
            f1         f2      corr
324  bill_amt2  bill_amt1  0.951484
400  bill_amt5  bill_amt6  0.946197
375  bill_amt4  bill_amt5  0.940134
349  bill_amt3  bill_amt2  0.928326
350  bill_amt3  bill_amt4  0.923969
423  bill_amt6  bill_amt4  0.900941
326  bill_amt2  bill_amt4  0.892482
301  bill_amt1  bill_amt3  0.892279
398  bill_amt5  bill_amt3   0.88391
372  bill_amt4  bill_amt1  0.860272
Index(['id', 'limit_bal', 'sex', 'education', 'marriage', 'age', 'pay_0',
       'pay_2', 'pay_3', 'pay_4', 'pay_5', 'pay_6', 'bill_amt1', 'bill_amt2',
       'bill_amt3', 'bill_amt4', 'bill_amt5', 'bill_amt6', 'pay_amt1',
       'pay_amt2', 'pay_amt3', 'pay_amt4', 'pay_amt5', 'pay_amt6', 'default'],
      dtype='object')
```

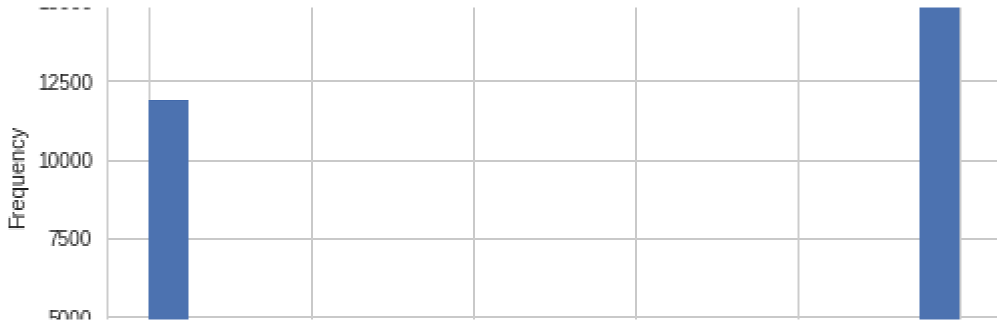
Skewed / Imbalanced data

```python
for i in data_clean.columns:
    data_clean.loc[:, i].plot(kind="hist", bins=20)
    plt.show()
```


Frequency
1400
1200
1000
800
600
400
200
0
0
5000
10000
15000
20000
25000
30000


Frequency
8000
7000
6000
5000
4000
3000
2000
1000
0
0
200000
400000
600000
800000
1000000


17500
15000



Final dataset

```
data_clean.describe()
```

	id	limit_bal	sex	education	marriage	age	pay_0	pay_2
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000
mean	15000.500000	167484.322667	1.603733	1.842267	1.557267	35.485500	-0.016700	-0.133767
std	8660.398374	129747.661567	0.489129	0.744494	0.521405	9.217904	1.123802	1.197186
min	1.000000	10000.000000	1.000000	1.000000	1.000000	21.000000	-2.000000	-2.000000
25%	7500.750000	50000.000000	1.000000	1.000000	1.000000	28.000000	-1.000000	-1.000000
50%	15000.500000	140000.000000	2.000000	2.000000	2.000000	34.000000	0.000000	0.000000
75%	22500.250000	240000.000000	2.000000	2.000000	2.000000	41.000000	0.000000	0.000000
max	30000.000000	1000000.000000	2.000000	4.000000	3.000000	79.000000	8.000000	8.000000

8 rows × 25 columns

```
data_clean.columns
```

```
Index(['id', 'limit_bal', 'sex', 'education', 'marriage', 'age', 'pay_0',
```

Notes for training

- convert columns: sex, education, marriage to categorical
- power transform (log) columns: limit_bal, bill_amtx, pay_amtx

Save datasets

```
loc = "/content/gdrive/My Drive/Colab Notebooks/uci-credit-card-defaults/data/defaults_clean.csv"
data_clean.to_csv(loc, index=False)
# verify file saved correctly
data_clean_load = pd.read_csv(loc)
assert data_clean_load.shape == data_clean.shape
```