- A. It's likely that the dataset is skewed. Exploratory data analysis will highlight any data cleaning problems and outliers.
- B. I would report the median for this dataset because it is more resistant to outliers.
- C. 284

In [1]:
```
#Import Python Libraries
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:
```
#Read csv file
df_orig = pd.read_csv("./2019 Winter Data Science Intern Challenge Data Set.csv")
df = df_orig
```

In [3]:
```
#Quick glance of the top 5 results
df.head()
```

Out[3]:

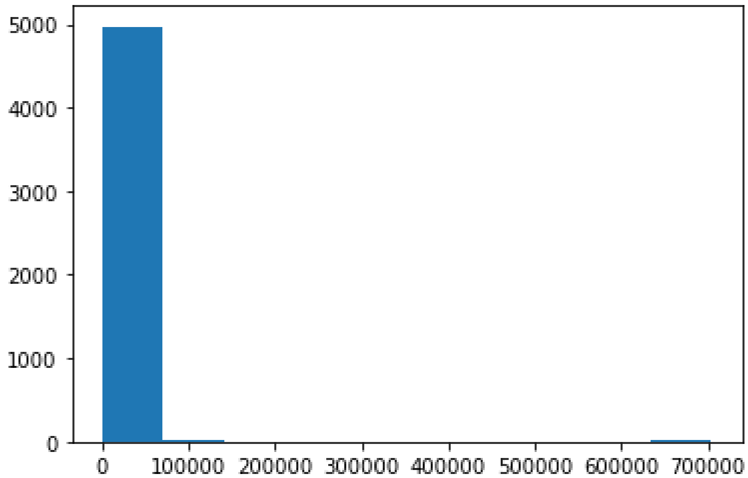
	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
0	1	53	746	224	2	cash	2017-03-13 12:36:56
1	2	92	925	90	1	cash	2017-03-03 17:38:52
2	3	44	861	144	1	cash	2017-03-14 4:23:56
3	4	18	935	156	1	credit_card	2017-03-26 12:43:37
4	5	18	883	156	1	credit_card	2017-03-01 4:35:11

In [4]:
```
#Get some baseline info about each value, including possible null values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   order_id        5000 non-null   int64
 1   shop_id         5000 non-null   int64
 2   user_id         5000 non-null   int64
 3   order_amount    5000 non-null   int64
 4   total_items     5000 non-null   int64
 5   payment_method  5000 non-null   object
 6   created_at      5000 non-null   object
dtypes: int64(5), object(2)
memory usage: 273.6+ KB
```

There are no null values, and the data types are sufficient for our analysis. Let's start by checking our hypothesis that the data is skewed with a histogram.

In [5]:
```
#Check normality of order_amount
plt.hist(df['order_amount']) # A histogram
plt.show()
```



This data is heavily skewed, which is inflating the mean of this dataset. We most likely should consider the median. Let's dive in to the descriptive statistics to make sure...

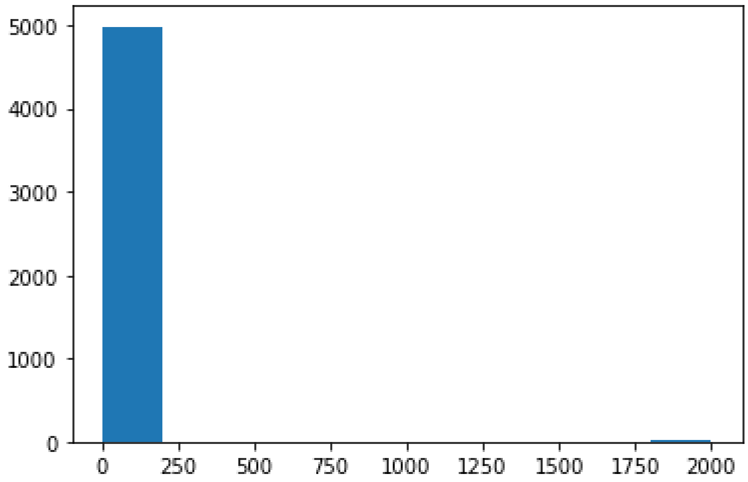
In [6]:
```
#Let's look at some descriptive statistics
df.describe()
```

Out[6]:

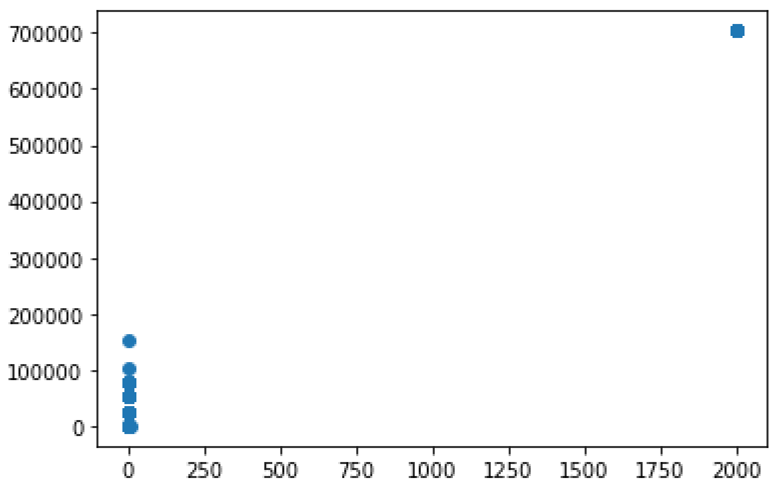
	order_id	shop_id	user_id	order_amount	total_items
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.00000
mean	2500.500000	50.078800	849.092400	3145.128000	8.78720
std	1443.520003	29.006118	87.798982	41282.539349	116.32032
min	1.000000	1.000000	607.000000	90.000000	1.00000
25%	1250.750000	24.000000	775.000000	163.000000	1.00000
50%	2500.500000	50.000000	849.000000	284.000000	2.00000
75%	3750.250000	75.000000	925.000000	390.000000	3.00000
max	5000.000000	100.000000	999.000000	704000.000000	2000.00000

The median (284) seems like a more appropriate measure of central tendency given the nature of the product. It looks like 75% of users are ordering 3 items or less, let's get some insight into these orders.

In [7]:
```
#Check normality of total_items 10
plt.hist(df['total_items']) # A histogram
plt.show()
```



In [8]:
```
#Let's look at order amount vs. total items
plt.scatter(df['total_items'], df['order_amount']) # A scatterplot
plt.show()
```



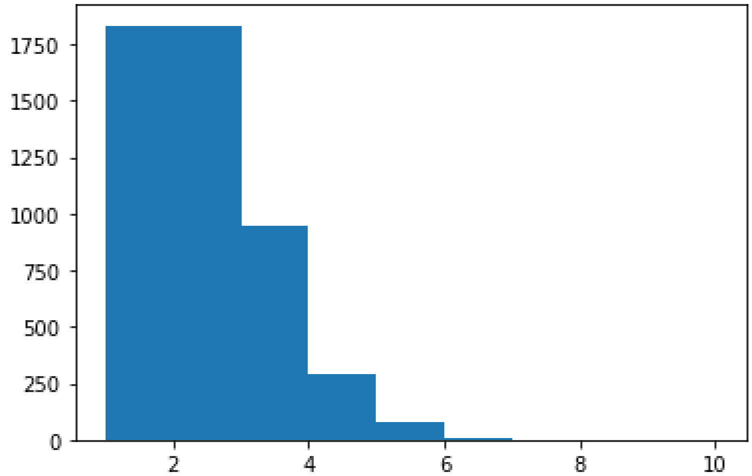
In [9]:
```
#Let's look at orders with a quantity greater than 3
df.loc[df['total_items'] > 3].describe()
```

Out[9]:

	order_id	shop_id	user_id	order_amount	total_items
count	397.000000	397.000000	397.000000	397.000000	397.000000
mean	2435.642317	49.372796	833.894207	31402.181360	89.720403
std	1436.831567	28.091249	96.321583	142741.610268	404.555030
min	16.000000	1.000000	607.000000	360.000000	4.000000
25%	1257.000000	26.000000	764.000000	536.000000	4.000000
50%	2394.000000	48.000000	830.000000	632.000000	4.000000
75%	3610.000000	70.000000	916.000000	712.000000	5.000000
max	4981.000000	100.000000	999.000000	704000.000000	2000.000000

Almost 20% of orders have more than 3 total items, but over 75% of those are still 5 items or less. Let's dig in a little more

In [10]:
```
#Check normality of total_items 10 or less
plt.hist(df['total_items'], bins = [1,2,3,4,5,6,7,8,9,10]) # A histogram
plt.show()
```



It seems that most orders have less than 10 items. The dataset is still right-skewed. While unnecessary, I can't help but be curious about the outliers that are greater than 10.

In [11]:
```
#Let's look at orders with a total_items greater than 10
df.loc[df['total_items'] > 10].describe()
```

Out[11]:

	order_id	shop_id	user_id	order_amount	total_items
count	17.000000	17.0	17.0	17.0	17.0
mean	2336.235294	42.0	607.0	704000.0	2000.0
std	1603.584872	0.0	0.0	0.0	0.0
min	16.000000	42.0	607.0	704000.0	2000.0
25%	1363.000000	42.0	607.0	704000.0	2000.0
50%	2154.000000	42.0	607.0	704000.0	2000.0
75%	3333.000000	42.0	607.0	704000.0	2000.0
max	4883.000000	42.0	607.0	704000.0	2000.0

User 607 made 17 purchases of 2000 items from shop 42. This seems like an outlier, let's check what happens to our descriptive statistics when we disregard this user:

In [12]:
```
#Descriptive statistics without user 607
df.loc[df['user_id'] != 607].describe()
```

Out[12]:

	order_id	shop_id	user_id	order_amount	total_items
count	4983.000000	4983.000000	4983.000000	4983.000000	4983.00000
mean	2501.060405	50.106362	849.918322	754.091913	1.99398
std	1443.090253	29.051718	86.800308	5314.092293	0.98318
min	1.000000	1.000000	700.000000	90.000000	1.00000
25%	1250.500000	24.000000	776.000000	163.000000	1.00000

	order_id	shop_id	user_id	order_amount	total_items
50%	2502.000000	50.000000	850.000000	284.000000	2.00000
75%	3750.500000	75.000000	925.000000	390.000000	3.00000
max	5000.000000	100.000000	999.000000	154350.000000	8.00000

When we disregard this user, the mean order value is 754; however, the data is still right-skewed. The median purchase order stays the same at 284, supporting our hypothesis that median is a better measure of central tendency for this data.

Interestingly, a max of 154350 seems exceptional. What's going with a purchase for $154,350, and 8 items or less?

In [13]:
```
#First, let's look at orders without user 607
df.loc[df['user_id'] != 607].sort_values(['order_amount'], ascending=False).head(10)
```

Out[13]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
691	692	78	878	154350	6	debit	2017-03-27 22:51:43
2492	2493	78	834	102900	4	debit	2017-03-04 4:37:34
3724	3725	78	766	77175	3	credit_card	2017-03-16 14:13:26
1259	1260	78	775	77175	3	credit_card	2017-03-27 9:27:20
4420	4421	78	969	77175	3	debit	2017-03-09 15:21:35
2564	2565	78	915	77175	3	debit	2017-03-25 1:19:35
2906	2907	78	817	77175	3	debit	2017-03-16 3:45:46
4715	4716	78	818	77175	3	debit	2017-03-05 5:10:44
3403	3404	78	928	77175	3	debit	2017-03-16 9:45:05
4192	4193	78	787	77175	3	credit_card	2017-03-18 9:25:32

Shop 78 seems to have exceptionally large order amounts

In [14]:
```
df.loc[df['shop_id'] == 78].describe()
```

Out[14]:

	order_id	shop_id	user_id	order_amount	total_items
count	46.000000	46.0	46.000000	46.000000	46.000000
mean	2663.021739	78.0	867.739130	49213.043478	1.913043
std	1338.520020	0.0	81.314871	26472.227449	1.029047
min	161.000000	78.0	707.000000	25725.000000	1.000000
25%	1428.250000	78.0	812.500000	25725.000000	1.000000
50%	2796.500000	78.0	866.500000	51450.000000	2.000000
75%	3720.250000	78.0	935.750000	51450.000000	2.000000
max	4919.000000	78.0	997.000000	154350.000000	6.000000

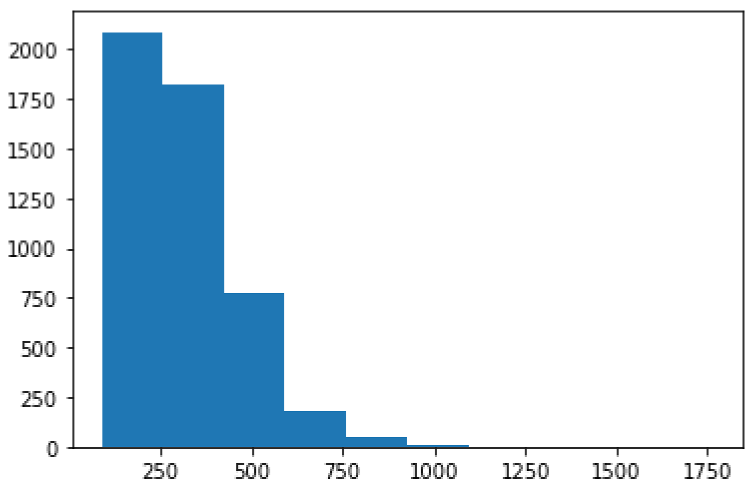
Let's see how our data looks when we disregard shop 78 and user 607

In [15]:
```
#Descriptive statistics without user 607
df2 = df.loc[(df['user_id'] != 607) & (df['shop_id'] != 78)]
df2.describe()
```

Out[15]:

	order_id	shop_id	user_id	order_amount	total_items
count	4937.000000	4937.000000	4937.000000	4937.000000	4937.000000
mean	2499.551347	49.846465	849.752279	302.580514	1.994734
std	1444.069407	29.061131	86.840313	160.804912	0.982821
min	1.000000	1.000000	700.000000	90.000000	1.000000
25%	1248.000000	24.000000	775.000000	163.000000	1.000000
50%	2497.000000	50.000000	850.000000	284.000000	2.000000
75%	3751.000000	74.000000	925.000000	387.000000	3.000000
max	5000.000000	100.000000	999.000000	1760.000000	8.000000

In [16]:
```
#Check normality of order amount without user 607 and shop 78
plt.hist(df2['order_amount']) # A histogram
plt.show()
```



After removing user 607 and shop 78, the mean order amount is 303, much more similar to the median of 284. While we've removed these outliers, the data is still right-skewed, supporting the need to use the median instead of the mean.

I can't help but be curious about user 607 and shop 78. Let's check to see if there is anything that we can identify...

In [17]:
```
#Shop 78 data
df.loc[df['shop_id'] == 78].sort_values(['order_amount'])
```

Out[17]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
160	161	78	990	25725	1	credit_card	2017-03-12 5:56:57
4584	4585	78	997	25725	1	cash	2017-03-25 21:48:44

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
4505	4506	78	866	25725	1	debit	2017-03-22 22:06:01
4040	4041	78	852	25725	1	cash	2017-03-02 14:31:12
3780	3781	78	889	25725	1	cash	2017-03-11 21:14:50
3440	3441	78	982	25725	1	debit	2017-03-19 19:02:54
3151	3152	78	745	25725	1	credit_card	2017-03-18 13:13:07
3085	3086	78	910	25725	1	cash	2017-03-26 1:59:27
2922	2923	78	740	25725	1	debit	2017-03-12 20:10:58
2548	2549	78	861	25725	1	cash	2017-03-17 19:36:00
2270	2271	78	855	25725	1	credit_card	2017-03-14 23:58:22
1452	1453	78	812	25725	1	credit_card	2017-03-17 18:09:54
2773	2774	78	890	25725	1	cash	2017-03-26 10:36:43
1056	1057	78	800	25725	1	debit	2017-03-15 10:16:45
1419	1420	78	912	25725	1	cash	2017-03-30 12:23:43
1193	1194	78	944	25725	1	debit	2017-03-16 16:38:26
1204	1205	78	970	25725	1	credit_card	2017-03-17 22:32:21
4918	4919	78	823	25725	1	cash	2017-03-15 13:26:46
1384	1385	78	867	25725	1	cash	2017-03-17 16:38:06
2512	2513	78	935	51450	2	debit	2017-03-18 18:57:13
490	491	78	936	51450	2	debit	2017-03-26 17:08:19
493	494	78	983	51450	2	cash	2017-03-16 21:39:35
4412	4413	78	756	51450	2	debit	2017-03-02 4:13:39
4311	4312	78	960	51450	2	debit	2017-03-01 3:02:10
4079	4080	78	946	51450	2	cash	2017-03-20 21:14:00
511	512	78	967	51450	2	cash	2017-03-09 7:23:14
617	618	78	760	51450	2	cash	2017-03-18 11:18:42
3705	3706	78	828	51450	2	credit_card	2017-03-14 20:43:15
2495	2496	78	707	51450	2	cash	2017-03-26 4:38:52
3167	3168	78	927	51450	2	cash	2017-03-12 12:23:08
1529	1530	78	810	51450	2	cash	2017-03-29 7:12:01
2452	2453	78	709	51450	2	cash	2017-03-27 11:04:04
2821	2822	78	814	51450	2	cash	2017-03-02 17:13:25
2818	2819	78	869	51450	2	debit	2017-03-17 6:25:51
3101	3102	78	855	51450	2	credit_card	2017-03-21 5:10:34

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
3724	3725	78	766	77175	3	credit_card	2017-03-16 14:13:26
2906	2907	78	817	77175	3	debit	2017-03-16 3:45:46
4192	4193	78	787	77175	3	credit_card	2017-03-18 9:25:32
4715	4716	78	818	77175	3	debit	2017-03-05 5:10:44
2690	2691	78	962	77175	3	debit	2017-03-22 7:33:25
4420	4421	78	969	77175	3	debit	2017-03-09 15:21:35
2564	2565	78	915	77175	3	debit	2017-03-25 1:19:35
1259	1260	78	775	77175	3	credit_card	2017-03-27 9:27:20
3403	3404	78	928	77175	3	debit	2017-03-16 9:45:05
2492	2493	78	834	102900	4	debit	2017-03-04 4:37:34
691	692	78	878	154350	6	debit	2017-03-27 22:51:43

Other than the price per item, nothing stands out. Perhaps it's worth looking at their site to see if there is something more there?

In [18]:

```
#Now let's look at User 607
df.loc[df['user_id'] == 607].sort_values(['created_at'])
```

Out[18]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
520	521	42	607	704000	2000	credit_card	2017-03-02 4:00:00
4646	4647	42	607	704000	2000	credit_card	2017-03-02 4:00:00
60	61	42	607	704000	2000	credit_card	2017-03-04 4:00:00
15	16	42	607	704000	2000	credit_card	2017-03-07 4:00:00
2297	2298	42	607	704000	2000	credit_card	2017-03-07 4:00:00
1436	1437	42	607	704000	2000	credit_card	2017-03-11 4:00:00
2153	2154	42	607	704000	2000	credit_card	2017-03-12 4:00:00
1362	1363	42	607	704000	2000	credit_card	2017-03-15 4:00:00
1602	1603	42	607	704000	2000	credit_card	2017-03-17 4:00:00
1562	1563	42	607	704000	2000	credit_card	2017-03-19 4:00:00
4868	4869	42	607	704000	2000	credit_card	2017-03-22 4:00:00
3332	3333	42	607	704000	2000	credit_card	2017-03-24 4:00:00
1104	1105	42	607	704000	2000	credit_card	2017-03-24 4:00:00
4882	4883	42	607	704000	2000	credit_card	2017-03-25 4:00:00
2835	2836	42	607	704000	2000	credit_card	2017-03-28 4:00:00
2969	2970	42	607	704000	2000	credit_card	2017-03-28 4:00:00
4056	4057	42	607	704000	2000	credit_card	2017-03-28 4:00:00

It seems strange that all of their purchases are made at exactly 4:00:00. Is there any relationship between user 607 and shop 42? Is there any relationship between shop 42 and time of purchase?

In [19]:
```
#Second, let's look at the shop
df.loc[df['shop_id'] == 42].sort_values(['user_id'])
```

Out[19]:

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
15	16	42	607	704000	2000	credit_card	2017-03-07 4:00:00
4646	4647	42	607	704000	2000	credit_card	2017-03-02 4:00:00
4056	4057	42	607	704000	2000	credit_card	2017-03-28 4:00:00
3332	3333	42	607	704000	2000	credit_card	2017-03-24 4:00:00
2969	2970	42	607	704000	2000	credit_card	2017-03-28 4:00:00
2835	2836	42	607	704000	2000	credit_card	2017-03-28 4:00:00
2297	2298	42	607	704000	2000	credit_card	2017-03-07 4:00:00
4868	4869	42	607	704000	2000	credit_card	2017-03-22 4:00:00
1602	1603	42	607	704000	2000	credit_card	2017-03-17 4:00:00
1562	1563	42	607	704000	2000	credit_card	2017-03-19 4:00:00
1436	1437	42	607	704000	2000	credit_card	2017-03-11 4:00:00
2153	2154	42	607	704000	2000	credit_card	2017-03-12 4:00:00
520	521	42	607	704000	2000	credit_card	2017-03-02 4:00:00
60	61	42	607	704000	2000	credit_card	2017-03-04 4:00:00
1362	1363	42	607	704000	2000	credit_card	2017-03-15 4:00:00
4882	4883	42	607	704000	2000	credit_card	2017-03-25 4:00:00
1104	1105	42	607	704000	2000	credit_card	2017-03-24 4:00:00
4767	4768	42	720	704	2	credit_card	2017-03-14 10:26:08
3513	3514	42	726	1056	3	debit	2017-03-24 17:51:05
4421	4422	42	736	704	2	credit_card	2017-03-01 12:19:49
1911	1912	42	739	704	2	cash	2017-03-07 5:42:52
2018	2019	42	739	352	1	debit	2017-03-01 12:42:26
979	980	42	744	352	1	debit	2017-03-12 13:09:04
2273	2274	42	747	704	2	debit	2017-03-27 20:48:19
1520	1521	42	756	704	2	debit	2017-03-22 13:10:31
308	309	42	770	352	1	credit_card	2017-03-11 18:14:39
1929	1930	42	770	352	1	credit_card	2017-03-17 8:11:13
4326	4327	42	788	704	2	debit	2017-03-16 23:37:57
834	835	42	792	352	1	cash	2017-03-25 21:31:25
40	41	42	793	352	1	credit_card	2017-03-24 14:15:41

	order_id	shop_id	user_id	order_amount	total_items	payment_method	created_at
1364	1365	42	797	1760	5	cash	2017-03-10 6:28:21
938	939	42	808	1056	3	credit_card	2017-03-13 23:43:45
4625	4626	42	809	352	1	credit_card	2017-03-11 8:21:26
2987	2988	42	819	1056	3	cash	2017-03-03 9:09:25
835	836	42	819	704	2	cash	2017-03-09 14:15:15
3651	3652	42	830	352	1	credit_card	2017-03-24 22:26:58
3697	3698	42	839	352	1	debit	2017-03-12 2:45:09
4294	4295	42	859	704	2	cash	2017-03-24 20:50:40
2491	2492	42	868	704	2	debit	2017-03-01 18:33:33
2609	2610	42	868	704	2	debit	2017-03-23 18:10:14
4745	4746	42	872	352	1	debit	2017-03-24 0:57:24
3998	3999	42	886	352	1	debit	2017-03-09 20:10:41
409	410	42	904	704	2	credit_card	2017-03-04 14:32:58
1471	1472	42	907	1408	4	debit	2017-03-12 23:00:22
1367	1368	42	926	1408	4	cash	2017-03-13 2:38:34
2003	2004	42	934	704	2	cash	2017-03-26 9:21:26
1512	1513	42	946	352	1	debit	2017-03-24 13:35:04
2053	2054	42	951	352	1	debit	2017-03-19 11:49:12
4231	4232	42	962	352	1	cash	2017-03-04 0:01:19
2766	2767	42	970	704	2	credit_card	2017-03-05 10:45:42
3903	3904	42	975	352	1	debit	2017-03-12 1:28:31

There's something interesting happening here specific to user 607 that merits review beyond the information we have...