In [15]:
```
#Import Packages

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px
import datetime
from datetime import datetime

#makes plotly plots render for github
from plotly.offline import download_plotlyjs, init_notebook_mode,  iplot
init_notebook_mode(connected=True)
```

For this assignmnet, we are looking at customer behavior data on an app like Harvest that tracks company hours, and tracks invoices sent and payments received.

First we will do an EDA on the data, and generate insights using the customer data, and then we will look at some business problems like customer conversion and churn.

In [2]:
```
#read the csvs
df_customers = pd.read_csv('customers.csv')
df_invoices =  pd.read_csv('invoices_and_payments.csv')
df_expenses = pd.read_csv('expenses.csv')

df_customers['converted_at_date'] = pd.to_datetime(df_customers['converted_at'], infe
df_invoices['invoice_created_at_date'] = pd.to_datetime(df_invoices['invoice_created_a
```

In [3]:
```
#Print size/shape of dataframes
print(df_customers.shape)
print(df_invoices.shape)
print(df_expenses.shape)
```

```
(15028, 27)
(5214607, 16)
(5659162, 7)
```

In [4]:
```
###################################################################
## CUSTOMERS EDA
###################################################################

display(df_customers.columns)

#check for duplicate rows
print('\nDUPLICATE ROWS:')
print(df_customers.duplicated().sum())

#check for duplicate company_id rows
print('\nDUPLICATE ROWS WITH company_id:')
print(df_customers['company_id'].duplicated().sum())

categorical_cols = ['billing_frequency',
       'primary_industry_grouped', 'purpose',
       'asana_enabled',
        'slack_oauths', 'xero_enabled',
       'quickbooks_enabled', 'stripe_enabled', 'tdd_enabled',
       'team_module_enabled', 'expense_module_enabled',
       'invoice_module_enabled', 'estimate_module_enabled',
       'client_dash_module_enabled', 'approval_module_enabled',
       'majority_platform', 'tracking_frequency']

#print unique values in each categorical column
print('\nUNIQUE VALUES IN EACH CATEGORICAL COLUMN:')
for col in df_customers:
    if col in categorical_cols:
        print(col,':', df_customers[col].unique())

#print columns that contain Null values
print('\nCOLUMNS THAT CONTAIN NULL VALUES:')
print(df_customers.isnull().sum()[df_customers.isnull().sum()>0])

#find inactive users
print('\nNUMBER OF ROWS RETURNING 0')
print('invoices:', len(df_customers[df_customers['invoices']==0]))
print('payments:', len(df_customers[df_customers['payments']==0]))
print('total_hours:', len(df_customers[df_customers['total_hours']==0]))
print('total_users:', len(df_customers[df_customers['total_users']==0]))
print('projects:', len(df_customers[df_customers['projects']==0]))


df_customers
```

```
Index(['company_id', 'converted_at', 'billing_frequency',
       'primary_industry_grouped', 'total_users', 'devices', 'purpose',
       'invoices', 'projects', 'payments', 'asana_enabled',
       'google_calendar_users', 'slack_oauths', 'xero_enabled',
       'quickbooks_enabled', 'stripe_enabled', 'tdd_enabled',
       'team_module_enabled', 'expense_module_enabled',
       'invoice_module_enabled', 'estimate_module_enabled',
       'client_dash_module_enabled', 'approval_module_enabled', 'total_hours',
       'majority_platform', 'tracking_frequency', 'converted_at_date'],
      dtype='object')
DUPLICATE ROWS:
0

DUPLICATE ROWS WITH company_id:
0

UNIQUE VALUES IN EACH CATEGORICAL COLUMN:
billing_frequency : ['yearly' 'monthly']
primary_industry_grouped : ['_other' '_unknown' 'tech' 'marketing' 'architecture' 'non
profit'
 'management consulting' 'engineering' 'design' 'healthcare' 'legal'
 'visual arts' 'construction' 'writing' 'accounting' 'events'
 'real estate' 'education' 'manufacturing' 'virtual assistant' 'music'
 'entertainment' 'ecommerce' 'retail' 'hospitality' 'research'
 'agriculture']
purpose : ['none' 'team' 'personal']
asana_enabled : [0 1]
slack_oauths : [0 1 2]
xero_enabled : [0 1]
quickbooks_enabled : [0 1]
stripe_enabled : [0 1]
tdd_enabled : [1 0]
team_module_enabled : [1 0]
expense_module_enabled : [1 0]
invoice_module_enabled : [1 0]
estimate_module_enabled : [0 1]
client_dash_module_enabled : [0 1]
approval_module_enabled : [1 0]
majority_platform : ['web' 'native' nan 'mix' 'other' 'integration' 'api']
tracking_frequency : ['weekly' 'daily' 'infrequently' 'monthly' 'work_daily' 'never']

COLUMNS THAT CONTAIN NULL VALUES:
majority_platform    811
dtype: int64

NUMBER OF ROWS RETURNING 0
invoices: 4514
payments: 6109
total_hours: 811
total_users: 8
projects: 151
```

Out[4]:

	company_id	converted_at	billing_frequency	primary_industry_grouped	total_users	devices	purpose
0	315309	2014-07-11 18:21:28 UTC	yearly	_other	0	14	none
1	438147	2015-08-27 19:58:50 UTC	yearly	_unknown	0	0	none
2	1156438	2020-09-04 07:18:11 UTC	yearly	tech	0	0	team
3	262929	2014-01-27 15:50:30 UTC	yearly	marketing	0	7	none
4	194227	2013-04-02 03:26:27 UTC	yearly	_unknown	0	2	none
...	...	...	...	...	...	...	...
15023	223993	2019-08-21 08:57:29 UTC	monthly	marketing	27	32	team
15024	203538	2013-04-30 12:50:26 UTC	monthly	tech	27	90	none
15025	526538	2016-06-16 21:35:57 UTC	monthly	tech	27	41	none
15026	409087	2015-05-06 08:27:42 UTC	monthly	architecture	27	5	none
15027	233238	2015-07-29 18:16:17 UTC	monthly	tech	27	90	none

15028 rows × 27 columns

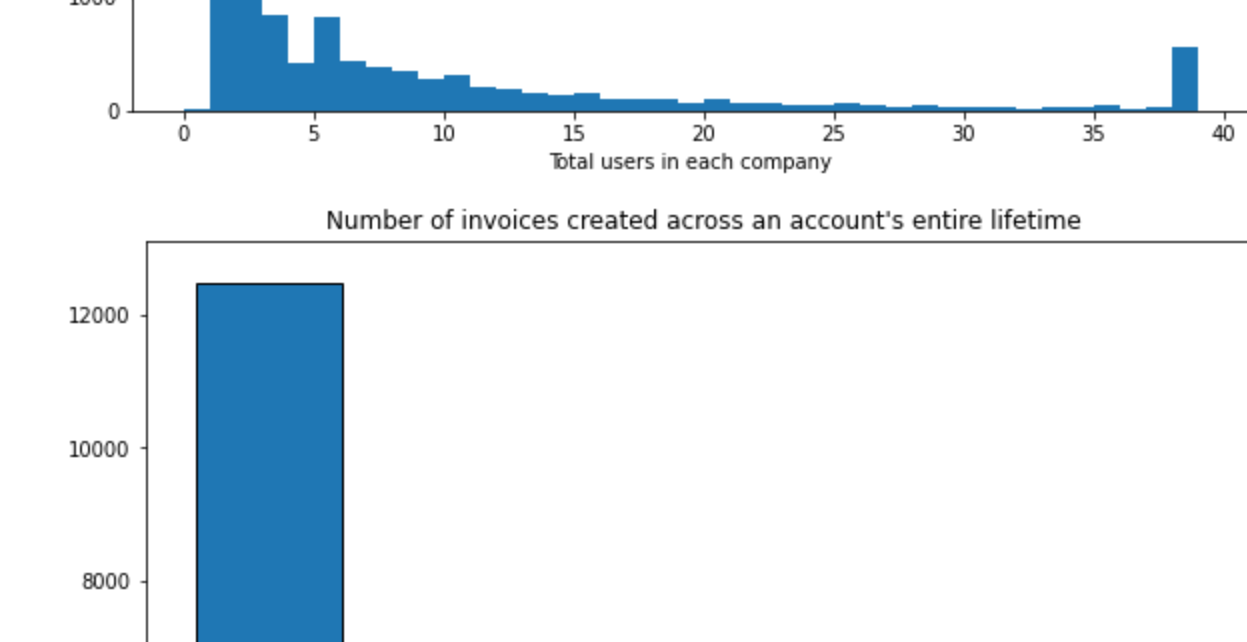
In [5]:
```
#SUMMARY OF TOTAL RESULTS

#lifetime totals
print('Total number of customers:', df_customers['company_id'].count())
print('Total number of invoices sent:', df_customers['invoices'].sum())
print('Total number of payments received:', df_customers['payments'].sum())
print('Total number of projects:', df_customers['projects'].sum())
print('Total number of hours logged:', df_customers['total_hours'].sum())
print('Total number of users:', df_customers['total_users'].sum())

#print mean, max, and min for continuous columns
cont_columns = ['total_users', 'invoices', 'projects', 'payments', 'total_hours']
print('\nTABLE SUMMARY')
display(df_customers[['total_users', 'invoices', 'projects', 'payments', 'total_hours
```

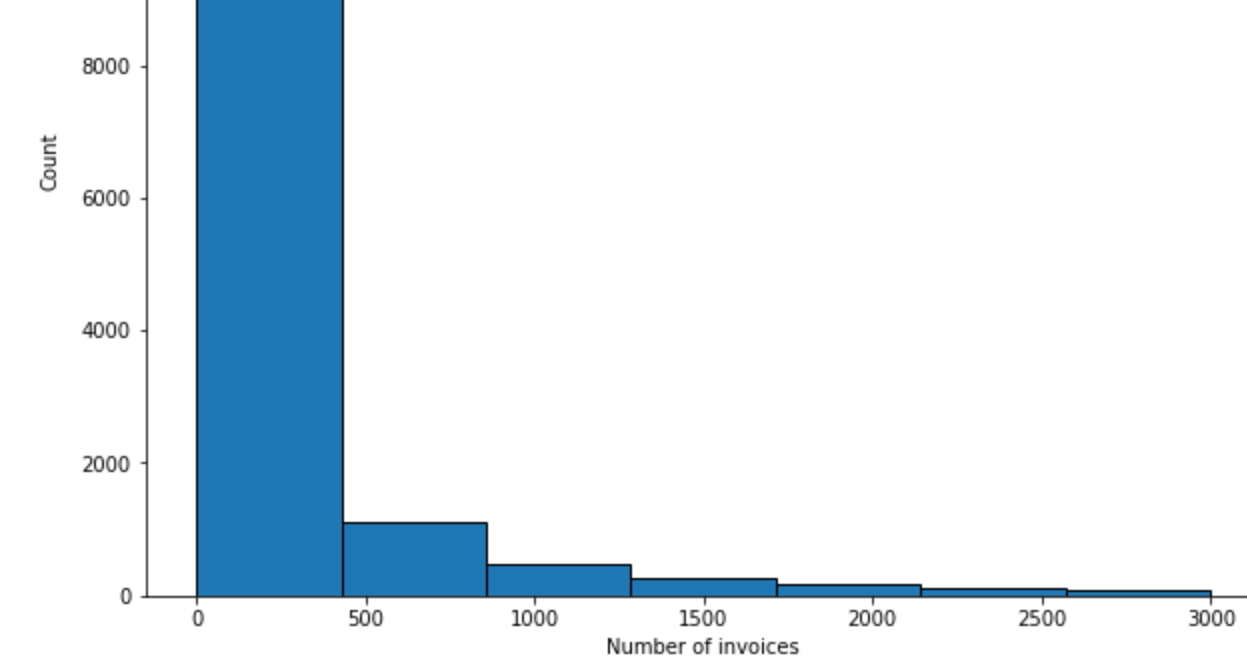
```
Total number of customers: 15028
Total number of invoices sent: 5054179
Total number of payments received: 4275499
Total number of projects: 4511062
Total number of hours logged: 419087684.2500009
Total number of users: 113558

TABLE SUMMARY
```

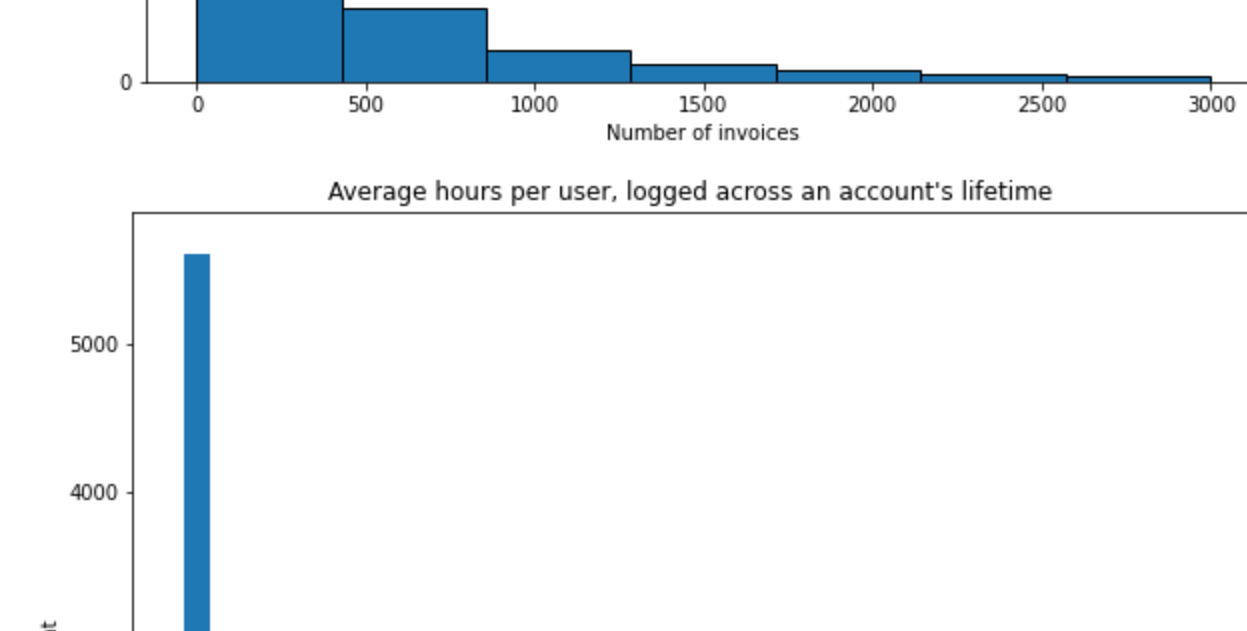
	total_users	invoices	projects	payments	total_hours
count	15028.000000	15028.000000	15028.000000	15028.000000	1.502800e+04
mean	7.556428	336.317474	300.177136	284.502196	2.788712e+04
std	20.082364	1232.339742	980.476202	1137.391476	9.549754e+04
min	0.000000	0.000000	0.000000	0.000000	0.000000e+00
25%	1.000000	0.000000	16.000000	0.000000	7.269975e+02
50%	2.000000	27.000000	62.000000	10.000000	3.823510e+03
75%	7.000000	235.000000	227.000000	183.000000	1.799153e+04
max	700.000000	75885.000000	58470.000000	71180.000000	5.676045e+06

Using the customer data, we will plot some insights related to the customer's and the type of accounts they hold and their industry, invoices, and customer conversions over time.

In [20]:
```
#plot number of customers vs purpose
purpose_counts = df_customers.groupby('purpose')[['company_id']].count().reset_index(
purpose_counts.columns = ['purpose', 'customer counts']
fig = px.bar(purpose_counts, x='purpose', y = 'customer counts', title='Count of custo

fig.update_layout(
    autosize=False,
    width=600,
    height=400)
# fig.show()
iplot(fig)

#plot number of customers vs primary_industry_grouped
industry_counts = df_customers.groupby(['primary_industry_grouped', 'purpose'])[['comp
industry_counts.columns = ['industry', 'purpose', 'customer counts']
fig = px.bar(industry_counts, x="industry", y="customer counts", color="purpose", titl
fig.update_layout(
    autosize=False,
    width=900,
    height=800)
# fig.show()
iplot(fig)

#plot TOTAL number of hours vs primary_industry_grouped
df = df_customers.groupby(['primary_industry_grouped'])[['total_users', 'invoices', 'p
fig = px.bar(df, x="primary_industry_grouped", y="total_hours", title="Total hours log
# fig.show()
iplot(fig)

#plot MEAN number of hours vs primary_industry_grouped
df = df_customers.groupby(['primary_industry_grouped'])[['total_users', 'invoices', 'p
df.columns = ['primary_industry_grouped','avg_no_users', 'avg_invoices', 'avg_no_proje
fig = px.bar(df, x="primary_industry_grouped", y="avg_hours", title="Average hours log
# fig.show()
iplot(fig)

#plot histogram of total users per company
plt.figure(figsize=(10,8))
bins = np.arange(0,40,1)
plt.hist(np.clip(df_customers['total_users'], bins[0], bins[-1]), bins=bins)
plt.xlabel("Total users in each company")
plt.ylabel("Counts")
plt.title("Histogram of total users per company")
plt.show()

#plot histogram of number of invoices sent per company
plt.figure(figsize=(10,8))
bins1=np.linspace(df_customers['invoices'].min(),3000, 8) #outlier in this column skew
plt.hist(df_customers['invoices'],bins=bins1, edgecolor='k',linewidth=1)
plt.xlabel("Number of invoices")
plt.ylabel("Count")
plt.title("Number of invoices created across an account's entire lifetime")
plt.show()

#plot histogram of average_hours spent per user per company
plt.figure(figsize=(10,8))
# bins1=np.linspace(df_customers['total_hours'].min(),200000, 10) #outlier in this co
bins = np.arange(0,40000,1000)
df_customers['average_hours']=df_customers['total_hours']/df_customers['total_users']
plt.hist(np.clip(df_customers['average_hours'], bins[0], bins[-1]), bins=bins)
plt.xlabel("Average number of hours")
plt.ylabel("Count")
plt.title("Average hours per user, logged across an account's lifetime")
plt.show()

#plot a time series of the number of companies that converted to paying customers
df_customers['converted_at_date'] = pd.to_datetime(df_customers['converted_at'], utc=
df = df_customers.groupby(pd.Grouper(key='converted_at_date', freq='M'))['company_id'
df.columns = ['converted_at_date', 'number_of_companies']
fig = px.line(df, x='converted_at_date', y="number_of_companies", title='Customer conv
# fig.show()
iplot(fig)


#plot a time series of the number of companies that converted to paying customers (ag
# df_customers['converted_at_date'] = pd.to_datetime(df_customers['converted_at'], ut
df = df_customers.groupby([pd.Grouper(key='converted_at_date', freq='M'), 'purpose'])
df.columns = ['converted_at_date', 'purpose','number_of_companies']
fig = px.line(df, x='converted_at_date', y="number_of_companies", color='purpose', tit
# fig.show()
iplot(fig)

#plot a time series of the number of companies that converted to yearly vs monthly pay
df = df_customers.groupby([pd.Grouper(key='converted_at_date', freq='M'), 'billing_fre
df.columns = ['converted_at_date', 'billing_frequency','number_of_companies']
fig = px.line(df, x='converted_at_date', y="number_of_companies", color='billing_frequ
# fig.show()
iplot(fig)
```







Number of customers vs the purpose

- There are more personal account types than team accounts on the platform; however, majority of the users select "None".

Number of customers vs the primary_industry_grouped

- Tech, marketing and management consulting dominate the known industry fields.

Total number of hours logged & average hours logged by industry

- While tech may have the most number of hours logged, the average hours logged graph shows us that manufacturing and engineering spend more time on the platform on average. Since the average hours is determined by the number of users in the team using the platform, it's more indicative of the usage than total hours.

Histogram of total users per company, total invoices sent, and average hours spent

- In all these graphs above, we see a long-tailed distribution, which makes sense because the distribution can't be below 0 and we expect anomolies (like time spent) to skew the data.

Time series of the number of companies that converted to paying customers by purpose, and by billing_frequency

- The customer conversion has substantially grown since 2006 - 2022. It appears that in Feb 2018, the company introduced the "purpose" feature which lets users determine wether their account is for personal or team uses. We can see that the personal account type is growing faster than the team account type. From the last graph, we see that the monthly billing frequency is much more popular than the yearly billing frequency.

Next, we will look at the invoices and expenses dataset & merge the two together.

In [7]:
```
###################################################################
# EXPENSES EDA
###################################################################

#Re-format expenses dataframe and add a few new features
billable_expenses_aggregated=df_expenses.loc[df_expenses['is_billable']==1,['company_i
billable_expenses_aggregated=billable_expenses_aggregated.rename(columns={'total_cost
nonbillable_expenses_aggregated=df_expenses.loc[df_expenses['is_billable']==0,['compar
nonbillable_expenses_aggregated=nonbillable_expenses_aggregated.rename(columns={'total

expenses_aggregated=pd.merge(billable_expenses_aggregated,nonbillable_expenses_aggrega
expenses_aggregated['billable_cost_percentage']=(100.0*expenses_aggregated['total_bill
expenses_aggregated['nonbillable_cost_percentage']=(100.0*expenses_aggregated['total_n

#Drop negative total billables/nonbillables
expenses_aggregated=expenses_aggregated.loc[(expenses_aggregated['billable_cost_percen
                                            (expenses_aggregated['nonbillable_cost_per

display(expenses_aggregated)

#We should convert all billable costs to a standardized currency (USD) in order to cor
#to do this, we should merge expenses_aggregated with the invoices dataframe in order
```

	company_id	invoice_id	total_billable_cost	total_billable_units	total_nonbillable_cost	total_nonbillable
0	1417	0	14634.19	85.00	34375.00	
1	1628	0	789.54	7.00	0.00	
2	2327	0	18134.42	1290.00	0.00	
3	2327	1	105245.49	40349.87	0.00	
4	2327	953657	1280.00	1.00	0.00	
...	...	...	...	...	...	
390924	1411306	0	0.00	0.00	44.82	
390925	1412117	0	0.00	0.00	2662.83	
390926	1414059	0	0.00	0.00	1720.00	
390927	1414483	0	0.00	0.00	265500.00	
390928	1416738	0	0.00	0.00	2855.34	

390716 rows × 8 columns

In [14]:
```
###################################################################
## INVOICES EDA
###################################################################

#Merge in the expenses_aggregated dataframe on company_id and invoice_id
df_invoices_and_expenses=pd.merge(df_invoices, expenses_aggregated, on=['company_id',
# Number of invoice data rows that merged with the expenses_aggregated dataframe
print("Percentage of invoice data with merged expenses information:",str(round(100.0*
display(df_invoices_and_expenses.head())
```

```
Percentage of invoice data with merged expenses information: 8.4%
```

	company_id	invoice_id	recurring_invoice_id	invoice_created_at	invoice_sent_at	invoice_state	invoice_amo
0	612957	25740109	NaN	2020-10-16 01:27:54 UTC	2020-10-16 01:35:40 UTC	open	384415
1	274327	14430600	NaN	2017-11-07 19:19:20 UTC	2017-11-07 19:20:06 UTC	open	22063
2	359036	33084769	NaN	2022-07-06 03:51:28 UTC	2022-07-04 05:00:00 UTC	open	28518
3	40237	10979856	NaN	2016-10-25 12:31:57 UTC	2016-10-27 09:20:33 UTC	open	7500
4	456494	30922632	NaN	2022-01-11 13:38:13 UTC	2022-01-11 13:38:18 UTC	open	180000

5 rows × 22 columns

Using the invoices data, we can take a look at when companies were last active by using the data they last sent an invoice (we could have also used payments). Since we don't have data with the times they logged in, we are going to assume the invoices give us an idea about their activity.

In [19]:
```
#plot a graph of companies vs the data of the last invoice sent
df = df_invoices.groupby('company_id')[['invoice_created_at']].max().reset_index()
df['invoice_created_at_date'] = pd.to_datetime(df['invoice_created_at'], utc=True)
df = df.groupby(pd.Grouper(key='invoice_created_at_date', freq='Y'))['company_id'].cou
df.columns = ['invoice_created_at_date', 'number_of_companies']

fig = px.bar(df, x='invoice_created_at_date', y="number_of_companies", title='Number o
# fig.show()

iplot(fig)
```

In [17]:

In [ ]:

In the next section, I will take a look at customer conversion and churn to see if we can develop any new insights using the data.

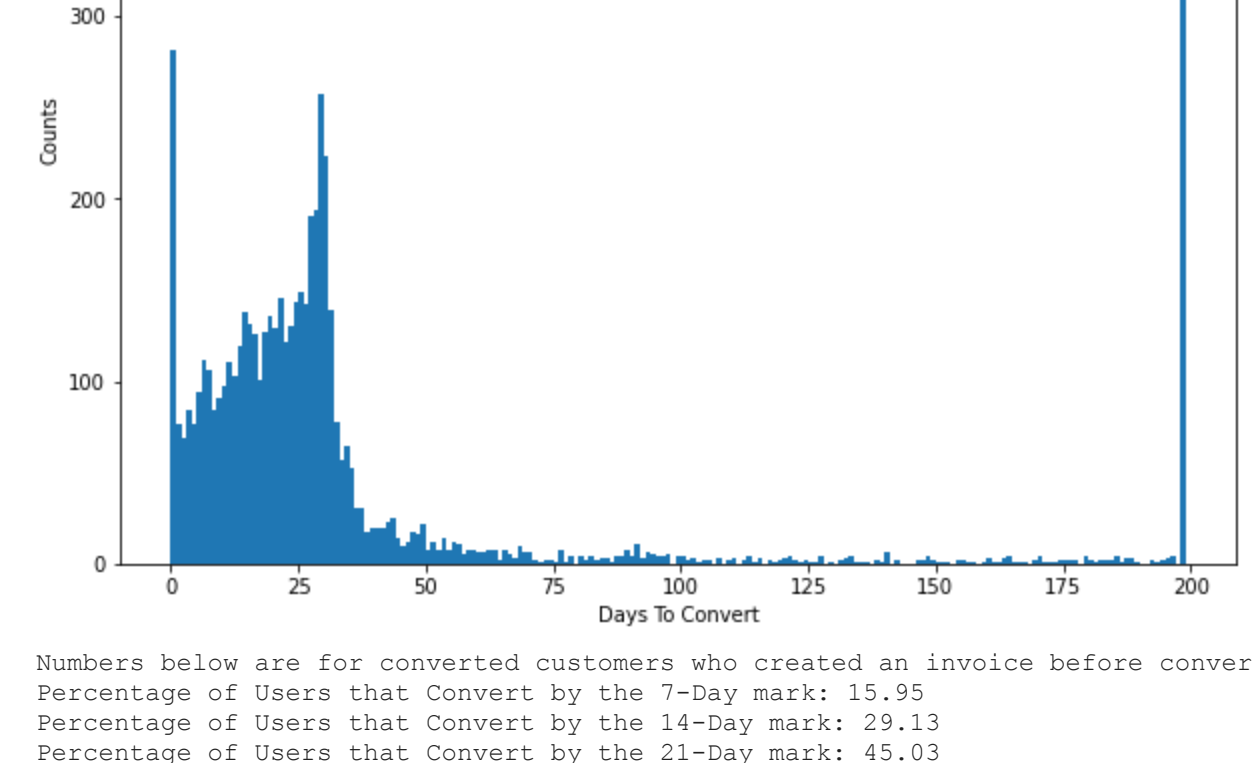
Customer Conversion

Since we don't have any data about the customer's behavior prior to the date they converted (ex. when they first joined the platform), we have to make some assumptions. We are going to assume that the date they sent an invoice (prior to their conversion date) is their first day on the platform.

By calculating the days between their first invoice and the conversion date, we can calculate the length of time before a customer converts & plot it on a histogram to observe the distribution of this data.

In [10]:
```
#1) Customer Conversion

conversion_df=pd.merge(df_customers[['company_id','converted_at_date']].groupby('compa
          df_invoices_and_expenses[['company_id','invoice_created_at_date']].groupby('c
          on='company_id',how='left').dropna()

converted_df = conversion_df.loc[conversion_df['invoice_created_at_date']<conversion_c
converted_df['days_to_convert']=(converted_df['converted_at_date'] - converted_df['inv
# display(converted_df)

#plot histogram of total users per company
plt.figure(figsize=(10,8))
bins = np.arange(0,200,1)
plt.hist(np.clip(converted_df['days_to_convert'], bins[0], bins[-1]), bins=bins)
plt.xlabel("Days To Convert")
plt.ylabel("Counts")
plt.title("Histogram of Days To Convert")
plt.show()

print("Numbers below are for converted customers who created an invoice before convert
print("Percentage of Users that Convert by the 7-Day mark:",round(100.0*converted_df.
print("Percentage of Users that Convert by the 14-Day mark:",round(100.0*converted_df
print("Percentage of Users that Convert by the 21-Day mark:",round(100.0*converted_df
print("Percentage of Users that Convert by the 30-Day mark:",round(100.0*converted_df
print("Percentage of Users that Convert by the 60-Day mark:",round(100.0*converted_df
print("Percentage of Users that Convert by the 365-Day mark:",round(100.0*converted_d
```

```
&lt;ipython-input-10-22c98ecccf2&gt;:8: 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-docs/stable/use
r_guide/indexing.html#returning-a-view-versus-a-copy
```




```
Numbers below are for converted customers who created an invoice before converting:
Percentage of Users that Convert by the 7-Day mark: 15.95
Percentage of Users that Convert by the 14-Day mark: 29.13
Percentage of Users that Convert by the 21-Day mark: 45.03
```

```
Percentage of Users that Convert by the 30-Day mark: 72.53
Percentage of Users that Convert by the 60-Day mark: 86.11
Percentage of Users that Convert by the 365-Day mark: 94.43
```

The graph above shows data from customers who converted and their days to conversion. Again, since we don't have the date when they joined the platform as a free user, we are assuming that the first invoice date is the creation date. From the graph above, we see that for users who converted, 72% of them did so before 30 days. This is an interesting result that makes sense because Harvest has a 30 day free trial!

Unfortunately, we can't determine features that predict a customer will convert because we do not have the data for customers who churned before becoming a paying customer.

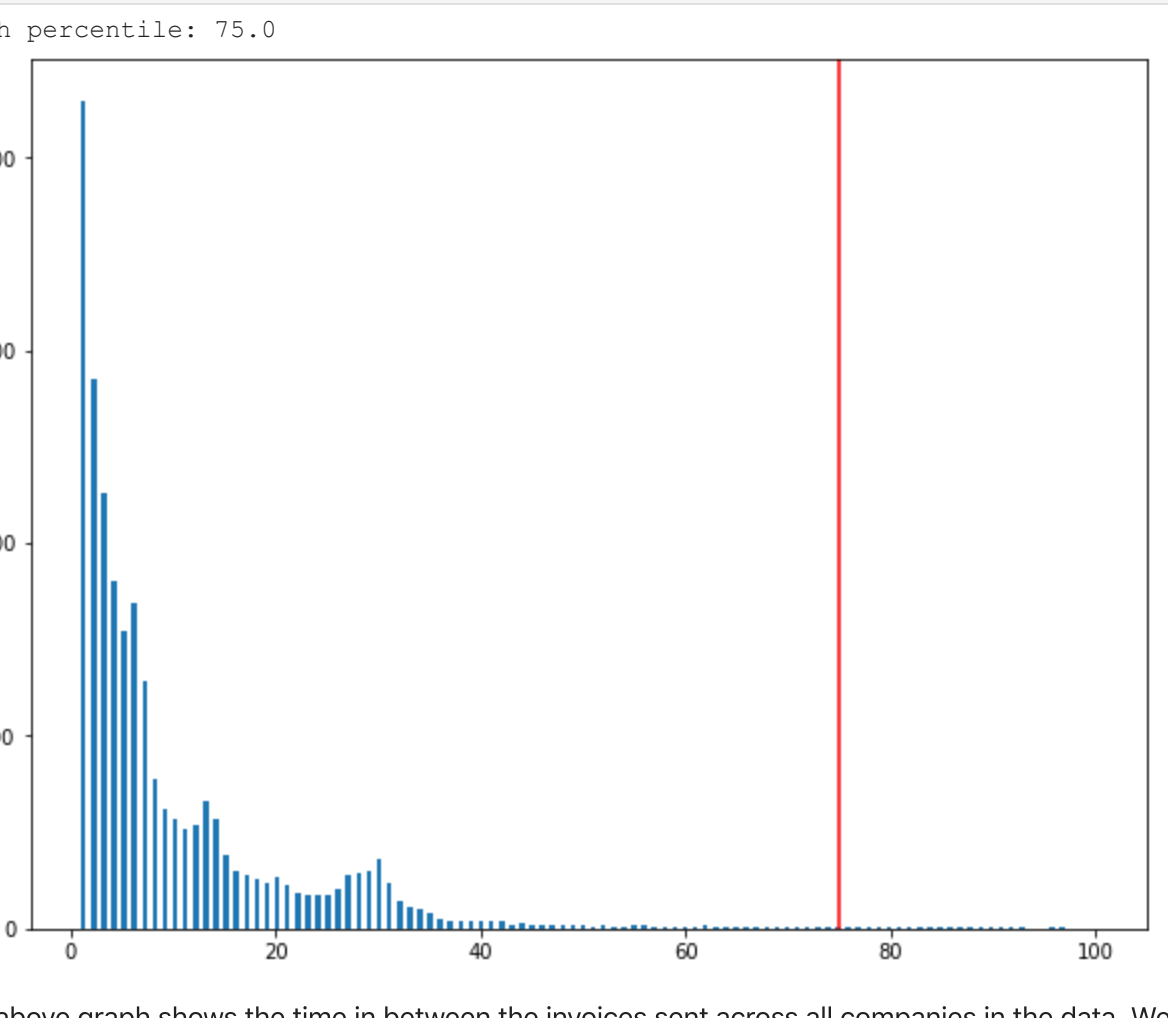
Customer Engagement Churn

Technically, we can't predict "churn" in the sense that a customer stopped paying and using the platform, but we can look at engagement churn. We have to make the following assumptions:

- Assumption 1: Churn is defined as a customer who haven't created an invoice in a specific number of days (to be determined)
- Assumption 2: Customers who churn on engagement don't return

In [11]:
```
#Create definition for Engagement Churn

def engagement_churn_level():
    dfstmp=[]
    for g in df_invoices_and_expenses[['company_id','invoice_created_at_date']].sort_v
        g[1]['days_between_invoices']=(g[1]['invoice_created_at_date']-g[1]['invoice_c
        dfstmp.append(g[1][['company_id','invoice_created_at_date','days_between_invo
    time_between_invoices_df=pd.concat(dfstmp,ignore_index=True).dropna()

    #plot histogram of time in between invoices sent
    plt.figure(figsize=(10,8))
    #Use 99th quantile to determine churn
    plt.hist(time_between_invoices_df['days_between_invoices'].sample(n=1000000),bins=
    q=np.quantile(time_between_invoices_df.loc[time_between_invoices_df['days_between_
    plt.axvline(q,color='r')
    print("99th percentile:",q)
    plt.show()

    return time_between_invoices_df,q

time_between_invoices_df,qfilter=engagement_churn_level()
```

```
99th percentile: 75.0
```



The above graph shows the time in between the invoices sent across all companies in the data. We can use anomoly detection to determine longer than usual time between invoices. The 99th percentile of this distribution corresponds to 75 days. We can determine that companies who haven't sent an invoice in over 75 days are churned (on engagement).

In [12]:
```
#find customers who haven't sent an invoice in over 75 days
churned_customers = time_between_invoices_df[time_between_invoices_df['days_between_i
churned_customers
```

Out[12]:

	company_id	invoice_created_at_date	days_between_invoices
2097	2945	2007-12-10 00:00:00+00:00	139.0
2253	2945	2013-08-28 01:00:55+00:00	131.0
2270	2945	2014-11-21 15:56:09+00:00	118.0
2271	2945	2015-03-10 02:34:34+00:00	108.0
2272	2945	2015-08-13 14:35:02+00:00	156.0
...	...	...	...
5209086	1372191	2022-07-04 22:41:04+00:00	126.0
5209891	1375418	2022-06-01 17:13:19+00:00	111.0
5210160	1377133	2022-06-15 12:42:42+00:00	119.0
5211425	1384731	2022-07-21 15:07:56+00:00	78.0
5212219	1390925	2022-07-18 14:04:18+00:00	113.0

13111 rows × 3 columns

In [21]:
```
#plot their churn rate over time

#plot a time series of the number of companies that converted to yearly vs monthly pa
df = churned_customers.groupby(pd.Grouper(key='invoice_created_at_date', freq='M'))['
df.columns = ['churned_date','number_of_companies']
fig = px.line(df, x='churned_date', y="number_of_companies", title='Time series of cu
# fig.show()
iplot(fig)
```

The graph above illustrates customer engagement churn over time, or in other words, customers who have not sent an invoice in 75 days. One thing to note is that customers can be double counted here, so if there are two periods of time that a customer hasn't sent an invoice for 75 days, then that customer will be counted twice.

Comparing this graph to the customer conversion graph, it appears that the rate of conversion is similar to engagement churn. Of course, this is a simplistic understanding of churn, and it's possible that customers may still be using the platform to log hours even if they are not sending invoices. Keeping that in mind, we can still suggest reminders to customers if they have not been "active" for a long period of time to increase retention.

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