ALCX Price vs ALCX Accounts

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How does the adoption of Alchemix impact price?

Data

Using Flipside's VELOCITY database, I created an SQL query (https://app.flipsidecrypto.com/shareable/adoption-and-price-J6iI1y) which allowed me to grab the number of unique ALCX wallets and ALCX price over time ranging from March 27, 2021 - April 11, 2021. Data used in the following analysis is all **realtime data**, based on VELOCITY's database which updates daily. Downloading the notebook and running locally would yield different results than what is shown below, as more data would be available.

Analysis

Imports

In [4]:
```
import urllib.request as rq
import json
from datetime import datetime
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

The main library used for this analysis is sklearn's linear regression module which allowed me to run linear regressions between three variables: price, ALCX accounts and time. The below code was used to grab the data from Flipside's API which imports the data in JSON as a list of dictionaries which I then converted to a pandas dataframe.

In [5]:
```
url = 'https://api.flipsidecrypto.com/api/v2/queries/4bf360e8-97ad-490f-b147-7024dffb13

try:
    dataset = rq.urlopen(url)
    dataset = dataset.read()
    dataset = json.loads(dataset)
    dataset = pd.DataFrame(dataset)
except Exception as e:
    print('Unable to get data from flipsidecrypto API. Check the URL below: \n{}'.forma
```

The next code block creates 3 additional series to the dataset:

- change in price

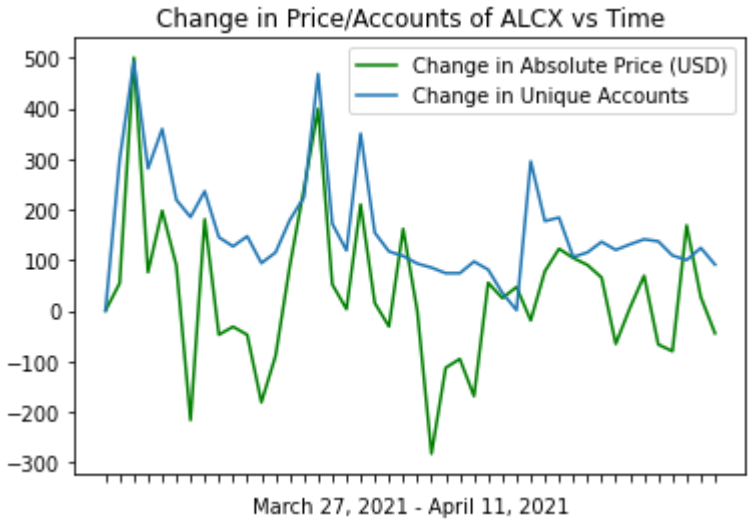
- change in unique addresses
- incrementing integers that represent number of days after launch These two series are used to plot the first figure below.

In [ ]:
```
#delta_price = [0]
#delta_addresses = [0]
ind = [0]
counter = 0
while counter < len(dataset)-1:
    ind.append(counter)
    dataset['BALANCE_DAY'][counter] = dataset['BALANCE_DAY'][counter].rsplit('T')[0]
    #delta_price.append(dataset['PRICE'][counter+1]-dataset['PRICE'][counter])
    #delta_addresses.append(dataset['UNIQUE_ADDRESSES'][counter+1]-dataset['UNIQUE_ADDR
    counter+=1
dataset['BALANCE_DAY'][counter] = dataset['BALANCE_DAY'][counter].rsplit('T')[0]
#dataset['DELTA_PRICE'] = delta_price
#dataset['DELTA_ADDRESSES'] = delta_addresses
dataset['IND'] = ind

dataset['DELTA_PRICE'] = np.gradient(dataset['PRICE'])
dataset['DELTA_ADDRESSES'] = np.gradient(dataset['DELTA_ADDRESSES'])

#del delta_addresses, delta_price, counter, ind
```

Change in Price/Unique Accounts of ALCX vs Time

See the following figure which shows the change in price and change in number of unique addresses with respect to time. From this graph, we can see that there is some correlation between the change in price and the change in unique accounts. From the graph, we can see that the maximas of the two series tend to line up, meaning that during a price surge, there will also be a jump in unique ALCX accounts. However, what does this mean over time?

In [9]:
```
#plot
fig,ax = plt.subplots()
plt.plot(dataset['BALANCE_DAY'],dataset['DELTA_PRICE'],label='Change in Absolute Price
plt.plot(dataset['BALANCE_DAY'],dataset['DELTA_ADDRESSES'],label='Change in Unique Acco
plt.legend(loc='best')
ax.axes.xaxis.set_ticklabels([])
plt.xlabel('March 27, 2021 - April 11, 2021')
plt.title('Change in Price/Accounts of ALCX vs Time')
plt.show()
```



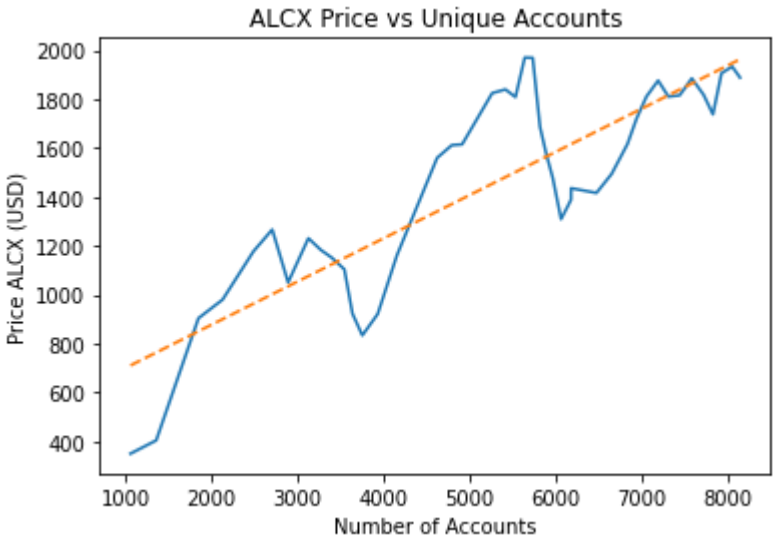
Change in Price vs Unique Accounts of ALCX

The below code snippet prepares the data to be used in sklearn's linear regression model which requires data to be in numpy arrays. For graphing purposes, integer values were used to days (x axis) to simplify graphing and allow the data to fit in the regression model. Beginning at 0 for launch, and incrementing to the length of the data.

In [10]:
```
x = dataset.iloc[:,5].values.reshape(-1,1)
y1 = dataset.iloc[:,1].values.reshape(-1,1)
y2 = dataset.iloc[:,2].values.reshape(-1,1)
linear_reg = LinearRegression()
linear_reg.fit(x,y1)
y_pred = linear_reg.predict(x)
linear_reg2 = LinearRegression()
linear_reg2.fit(x,y2)
y_pred2 = linear_reg2.predict(x)
lin_reag3 = LinearRegression()
lin_reag3.fit(y2,y1)
y_pred3 = lin_reag3.predict(y2)
```

The below graph represents the price of ALCX vs the number of unique addresses. From the below graph, we can see that the price of ALCX *tend* to increases with the amount of unique accounts. We can see near 3900 and 6000 accounts, there is a dip in price. However, we can see the overall trend of the data increase as the number of accounts.

In [13]:
```
fig,ax = plt.subplots()
plt.plot(dataset['UNIQUE_ADDRESSES'],dataset['PRICE'],label='Unique Addresses')
plt.plot(y2,y_pred3,linestyle='dashed')
plt.xlabel('Number of Accounts')
plt.ylabel('Price ALCX (USD)')
plt.title('ALCX Price vs Unique Accounts')
plt.show()
```



In [19]:
```
print(metrics.r2_score(y1,y_pred3))
```

```
0.7218622480566586
```

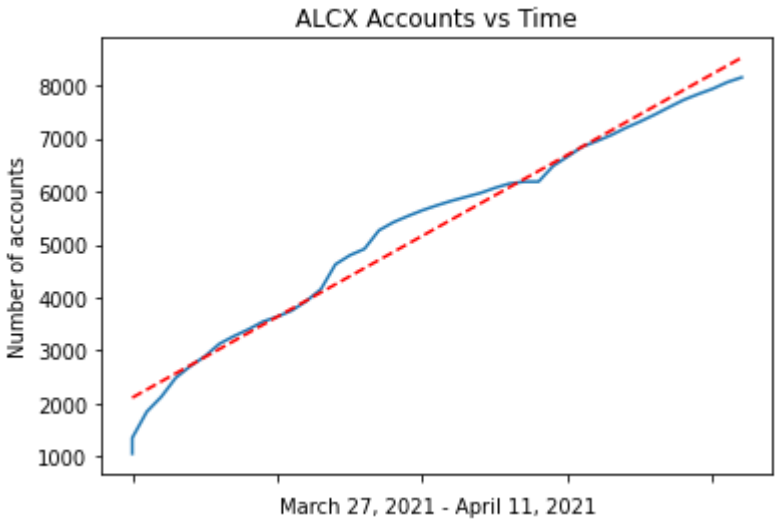
ALCX Accounts vs Time

Below represents the number of accounts with respect to time. It is evident that ALCX is steadily gaining users, brought in by outside factors. However, this poses additional questions (outside of the scope of this analysis) relating to the variables that affect the increase in adoption.

Is the price increase due to increase in accounts?

From the graphs, we can see taht the price fluctuates with respect to the addition of new wallets, however the rate of new wallets is more consistent. In addition, the change in price/accounts of ALCX vs time, shows during a large price jump, the number of accounts also jumps. Unfortunately, there isn't enough data to say for sure which one influences the other more.

In [12]:
```
fig,ax = plt.subplots()
plt.plot(x,y2,label='accounts (USD)')
plt.plot(x,y_pred2,color='r',linestyle='dashed')
ax.axes.xaxis.set_ticklabels([])
plt.xlabel('March 27, 2021 - April 11, 2021')
plt.ylabel('Number of accounts')
plt.title('ALCX Accounts vs Time')
plt.show()
```



In [20]:
```
print(metrics.r2_score(y2,y_pred2))
```

```
0.9731792743269163
```

Conclusion

With certainty, growth in price tends to be accompanied by a growth in adoption. However, each of these variables have outstanding factors as well such as current market trends, media exposure, and other external factors outside the scope of this analysis. An interesting continuation of this would be to incorporate these other variables into the equation, such as bounty #13: Twitter and ALCX.

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