PennyLane Search Exploratory Data Analysis

We will be exploring a dataset regarding the recent searches from PennyLane.ai/search. We will start by loading the data and getting a general idea of what kinds of data are including in the dataset.

In [1]:
```
#import required libraries
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns

#read in csv file of search data
df=pd.read_csv('/Users/lindsaybabcock/Documents/Work/Applications/Xanadu
```

In [2]:
```
#Change column to datetime types
df['created_at']=pd.to_datetime(df['created_at'],
                                format='%Y-%m-%d %H:%M:%S.%f')

#take a look at data types/data
df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 220524 entries, 0 to 220523
Data columns (total 11 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   id                    220524 non-null  object
 1   created_at            220524 non-null  datetime64[ns, UTC]
 2   query_text            19596 non-null   object
 3   total_results         220524 non-null  int64
 4   search_parameters     220524 non-null  object
 5   query_content_types   220456 non-null  object
 6   response_content_ids  220524 non-null  object
 7   role                  576 non-null     object
 8   survey                3095 non-null    object
 9   personas              3095 non-null    object
 10  persona_other         112 non-null     object
dtypes: datetime64[ns, UTC](1), int64(1), object(9)
memory usage: 18.5+ MB
```

Out[2]:

	id	created_at	query_text	total_results	search_parameters	query_cont
0	04c0a197-0cbc-4bca-b5d4-c6134ba49546	2024-08-08 21:25:44.101779+00:00	mikhail	4	{"sort": null, "limit": 16, "filter": "((type ...	
1	0b0369f3-2bc9-4aa2-9f92-27e8954d8c41	2024-08-08 21:54:19.770839+00:00	NaN	37	{"sort": ["published_at:desc"], "limit": 16, "...	
2	0d72dae5-3aac-469f-910b-a7b98597ef7d	2024-08-08 21:26:07.410746+00:00	mikhail	5	{"sort": null, "limit": 16, "filter": "((type ...	
3	0e4fb2dd-6d5d-449b-b6a3-374d5430534a	2024-08-08 21:26:50.247836+00:00	izaac	82	{"sort": null, "limit": 16, "filter": "((type ...	
4	17d8319b-360a-4bf5-84a6-f2b1c753a692	2024-08-08 22:07:49.601295+00:00	NaN	5343	{"sort": null, "limit": 16, "filter": "((type ...	

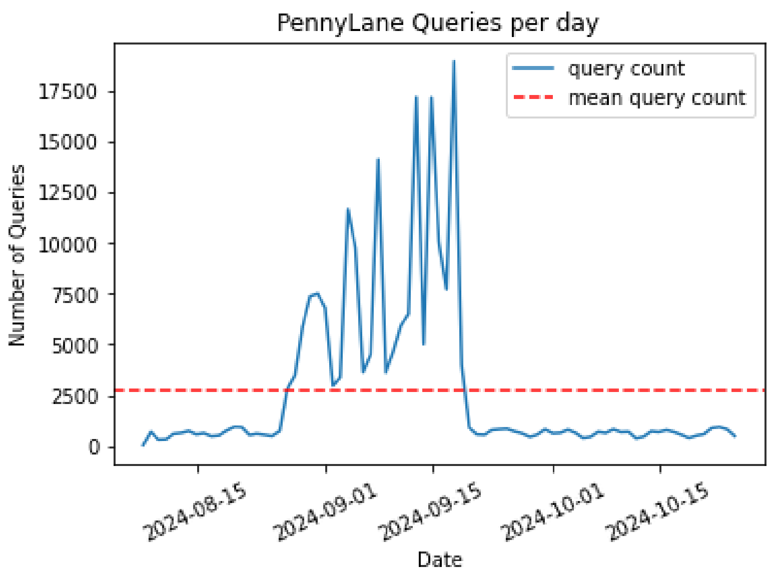
Search Traffic

Now that we have an idea of the data we are exploring, we will begin by looking at trends in the search traffic over time.

In [3]:
```
#Aggregate data to show searches per day
df['created_at'].dt.date.value_counts().plot(rot=25, title='PennyLane Qu
plt.axhline(df['created_at'].dt.date.value_counts().mean(),c='r',ls='--
plt.ylabel('Number of Queries')
plt.xlabel('Date')
plt.legend(['query count', 'mean query count']);

print('Searches per day:')
print(round(df['created_at'].dt.date.value_counts().describe()))
```

```
Searches per day:
count       79.0
mean      2791.0
std       4186.0
min         58.0
25%        590.0
50%        755.0
75%       3546.0
max      18935.0
Name: created_at, dtype: float64
```



In [4]:

```
#Show top queries during the time of the search traffic spike.
df_peak = df.loc[(df['created_at'] >= '2024-08-27') & (df['created_at']
print('Top searches during peak period:')
print(df_peak['query_text'].value_counts(dropna=False).rename_axis('Que

#Show top queries outside of the time of the search traffic spike.
df_nonpeak = df.loc[(df['created_at'] < '2024-08-27') | (df['created_at
print('Top searches outside of peak period:')
print(df_nonpeak['query_text'].value_counts(dropna=False).rename_axis('(
```

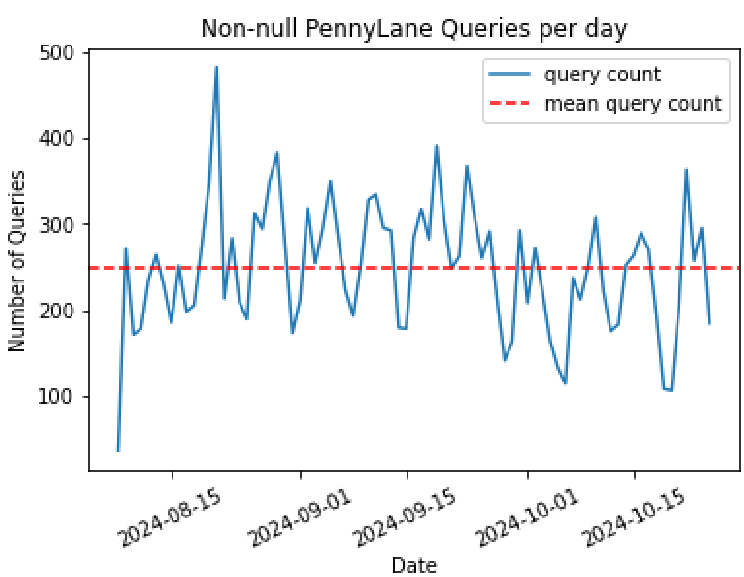
```
Top searches during peak period:
            Query   Count
0             NaN  174394
1            test    3010
2             vqe      71
3            qaoa      66
4  neural network      37
Top searches outside of peak period:
     Query  Count
0      NaN  26534
1     test   4622
2  quantum    192
3     qaoa    178
4      vqe    143
```

In [5]:
```
#create subset dataframe excluding nulls in the query text
df_text = df.dropna(subset=['query_text'])

#Aggregate data to show searches per day of non-null queries
df_text['created_at'].dt.date.value_counts().plot(rot=25, title='Non-nu
plt.axhline(df_text['created_at'].dt.date.value_counts().mean(),c='r',l
plt.ylabel('Number of Queries')
plt.xlabel('Date')
plt.legend(['query count', 'mean query count']);


print('Non-null searches per day:')
print(round(df_text['created_at'].dt.date.value_counts().describe()))
print('Total non-null searches: ', df_text.shape[0])
```

```
Non-null searches per day:
count     79.0
mean     248.0
std       74.0
min       36.0
25%      196.0
50%      252.0
75%      293.0
max      482.0
Name: created_at, dtype: float64
Total non-null searches:  19596
```



There was a significant increase in search traffic between late August to mid September. Looking more closely at what was being queried at this time, it appears searches containing text did not increase in the same way. I am unsure of what caused the spike in activity of null queries during this time, potentially site testing/development.

Removing the null queries brings the average queries per day down drastically from 2791 to 248. For the remainder of the analysis we will focus on queries containing text only.

In [7]:
```
#import warnings
#warnings.filterwarnings('ignore')

df_text['day_of_week']=df_text['created_at'].dt.dayofweek
df_text['hour_of_day']=df_text['created_at'].dt.hour

search_counts = df_text.groupby(['day_of_week', 'hour_of_day']).size().u
search_counts.index = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Fr

plt.figure(figsize=(12, 8))
sns.heatmap(search_counts, cbar_kws={'label': 'Total queries per Time Un
plt.title('Frequency of Queries by Day of Week and Hour of Day')
plt.xlabel('Hour of Day')
plt.ylabel('Day of Week')
plt.show()
```

I will be assuming that the 'created_at' times are recorded in the local time zone of the user. Here we see that the majority of queries are made during normal working hours - Monday to Friday, midday, suggesting that users of PennyLane are using it for work/school purposes.

Demographics

Below we will explore the distribution of demographics amongst users making queries on PennyLane.ai/search.

In [8]:
```
#Aggregate data to find percentage of users that log-in and use pennylai
df_text['survey'].value_counts(dropna=False, normalize=True).mul(100).r
```

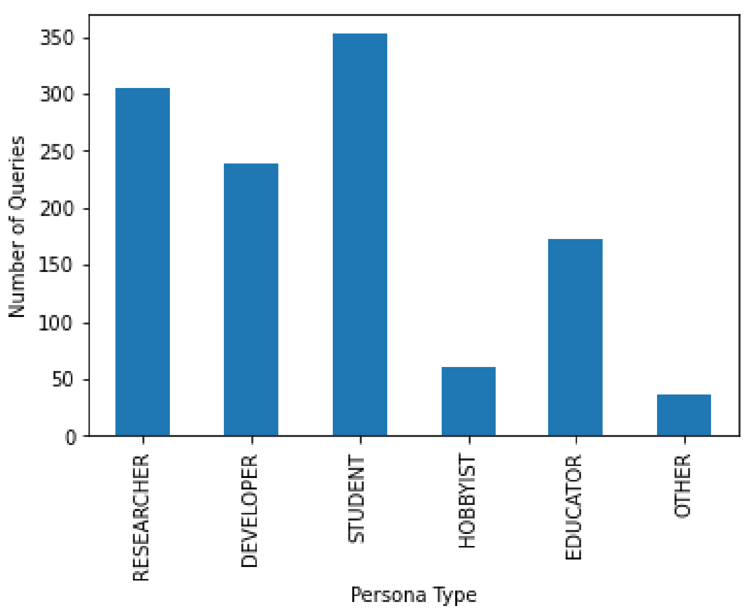
Out[8]:
```
NaN                            96.08%
{"uses_pennylane": true}        2.92%
{"uses_pennylane": false}        1.0%
Name: survey, dtype: object
```

96% of queries are done by users that are not signed in, thus we have little data about their specific roles. It may be useful to include features to encourage users to sign in/make accounts.

In [9]:
```
#Show distribution of personas
#print(df_text['personas'].unique())
persona_types = ['RESEARCHER','DEVELOPER','STUDENT','HOBBYIST','EDUCATOI
df_personas = pd.DataFrame(persona_types,columns=['type'])
df_personas['counts']=[df_text['personas'].str.contains(x).sum() for x :
df_personas.plot(kind='bar', x='type', legend=False)
plt.xlabel('Number of PennyLane Queries by Persona Type')
plt.xlabel('Persona Type')
plt.ylabel('Number of Queries')

#Show non-categorized personas
print(df_text['persona_other'].value_counts().rename_axis('persona_othe
```

```
              persona_other  Count
0         Community manager     28
1           Xanadu employee      5
2  Senior Product Manager        3
```



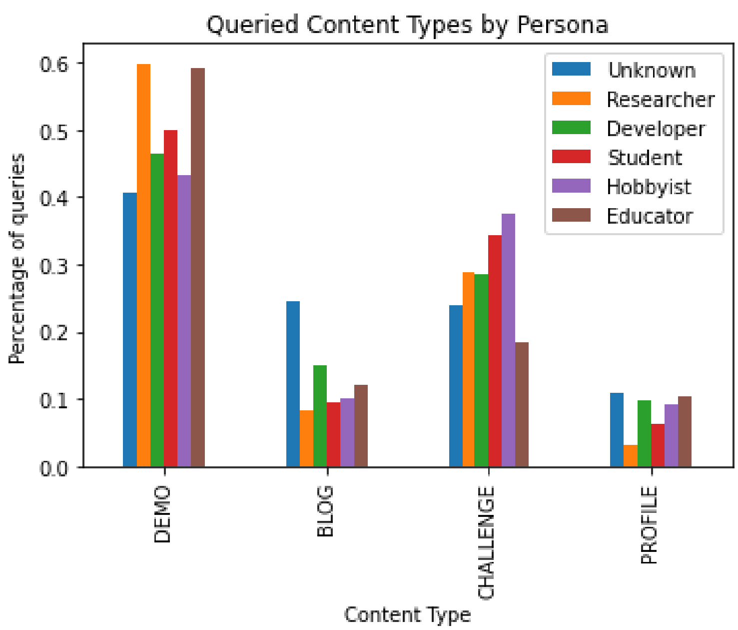
In [10]:
```
#create subset dataframes for various personas
df_researcher = df[df.personas.str.contains('RESEARCHER',na=False)]
df_developer = df[df.personas.str.contains('DEVELOPER',na=False)]
df_student = df[df.personas.str.contains('STUDENT',na=False)]
df_hobbyist = df[df.personas.str.contains('HOBBYIST',na=False)]
df_educator = df[df.personas.str.contains('EDUCATOR',na=False)]
#df_other = df[df.personas.str.contains("OTHER",na=False)] #choosing no

content_types = ['DEMO','BLOG','CHALLENGE','PROFILE']
personas_df = [df_text,df_researcher,df_developer,df_student,df_hobbyis

#count occurances of querys filtered for each content type for each pers
df_gen = pd.DataFrame(content_types,columns=['type'])
for dataframe in range(0,len(personas_df)):
    df_gen[dataframe]= [personas_df[dataframe]['query_content_types'].s
    df_gen[dataframe] = df_gen[dataframe]/df_gen[dataframe].sum()

#Show barplot of content types for each persona
df_gen.plot(kind='bar', x='type')
plt.legend(['Unknown','Researcher','Developer','Student','Hobbyist','Edu
plt.title('Queried Content Types by Persona')
plt.xlabel('Content Type')
plt.ylabel('Percentage of queries')
```

Out[10]: Text(0, 0.5, 'Percentage of queries')



The highest number of queries are made by Students, Researchers, and Developers. If we focus on supporting Reasearchers, as they are a high value persona, we can see that researchers are most often looking for demos, roughly 60% of the time, when searching PennyLane.ai. Focusing on providing high quality demo webpages would likely improve user experience for Researchers. On the other hand, researchers appear to be uninterested in profile or blog posts, searching for those types of content less than 10% of the time. For all groups, demos are most commonly searched for, therefore it may be beneficial to return them more often or closer to the top of the page for general queries without these filters on.

Top Queries

We can now explore what is being queried to understand the users top interests.

In [11]:
```
#Count which text items were queried the most
print('General top queries:')
print(df_text['query_text'].value_counts().rename_axis('query_text').res

print('Top queries of researchers:')
print(df_researcher['query_text'].value_counts().rename_axis('query_tex
```

```
General top queries:
                   query_text  Count
0                        test   7632
1                        qaoa    244
2                     quantum    228
3                         vqe    214
4                         qml    149
5      quantum neural network    113
6                 variational    109
7    quantum machine learning    101
8                       torch     84
9                 hamiltonian     81
10             neural network     80
11                       shor     78
12                        gpu     69
13           classical shadow     68
14                     kernel     68
Top queries of researchers:
                   query_text  Count
0         simulated annealing     12
1                        qaoa     11
2                 hamiltonian      9
3              phase kickback      8
4                     qmldata      8
5                optimization      7
6    quantum machine learning      7
7                         gpu      7
8                    photonic      6
9                    encoding      6
10                   kottmann      6
11                        vqe      5
12                     grover      5
13                certificate      5
14                      image      5
```

Looking at the top searches (ignoring 'test'), we can see that most often users are searching for items such as 'Quantum approximate optimization algorithm (QAOA)', 'Quantum Machine Learning (QML)', and 'Hamiltonian'. Researchers are also often searching for those items, as well as 'Simulated Annealing', 'Phase Kick-back', and 'Optimization'.

Next we can order query results by the total results returned for the query in ascending order, and the number of times researchers have searched them, in descending order. These results give us an idea of what concepts users are interested in that are lacking resources on the

PennyLane.ai website.

In [12]:
```
#Show lowest
df_totals=df_text.groupby(['query_text','total_results']).size().reset_i
df_totals=df_totals.sort_values(['total_results', 'count'], ascending =
print('Low result queries:')
print(df_totals.loc[df_totals['count'] > 1].head(20)) #exclude entries w

print('Low result queries for researchers:')
df_totals_research=df_researcher.groupby(['query_text','total_results']
df_totals_research=df_totals_research.sort_values(['total_results', 'cou
print(df_totals_research.loc[df_totals_research['count'] > 1].head(15))
```

```
Low result queries:
                              query_text  total_results  count
77                                  alan              0     19
5486                                 vqc              0     19
338                                 bb84              0     10
447   building molecular hamiltonians              0      9
897                         cryptography              0      8
2881                                 mqt              0      8
4421                                qubo              0      7
101                               alpine              0      6
261                          autoencoder              0      6
3568                                 qkd              0      6
600                                 cite              0      5
3726                                qpca              0      5
4584                                  rl              0      5
5278                                 tsp              0      5
1414                           federated              0      4
1656                                 gpu              0      4
1940                                 hhl              0      4
2917                                nasa              0      4
3343                     poissonboltzmann              0      4
3455                                qaoa              0      4
Low result queries for researchers:
                           query_text  total_results  count
182               womanium challenge              0      3
33                           diamond              0      2
40                               gpu              0      2
69                               iqc              0      2
114                             qaqo              0      2
127  quantum bit string comparator              0      2
82                     matt silverman              1      2
105                         photonic              1      2
178                              vqd              1      2
41                               gpu              2      2
149               simulated annealing              2      2
108                        photonics              3      2
176                              vqa              5      4
121                              qnn              5      2
42                               gpu              6      2
```

In general, there appear to be a fair number of searches for quantum cryptography related queries ('bb84','cryptography',qkd'), with zero returned results. Specifically for researchers there are more quantum hardware related queries such as 'photonics' or 'diamond'. It may be helpful for users if more resources on these topics were developed.

Further, certain results suggest user typos, such as 'qaqo', where the user is likely looking for 'qaoa'. Indicating potential room for improvement in the software for typo suggestion.

As with many datasets, futher exploratory analysis could be done, including but not limited to: expanding the top queries analysis to include the users filters on content type (ie. see if diamond+BLOG is more often queried than diamond+DEMO), as well as explore sorting filters on queries, and understanding which result content id are shown the most.

In [ ]:

```

```