date; find . | grep csv | while read full_path; do cat $full_path | awk -F, '$5 == "1" {print 0}' >> all_failures_all_smart__column_count_varies.log; done; date

count the number of columns in the file by counting commas per line

while read p; do echo p | tr -cd , | wc -c; done < all_failures_all_smart__column_count_varies.log Because the columns are inconsistent, check which columns are aligned date; find . | grep csv | while read full_path; do head -n1 $full_path >> all_column_headers.log; done; date Now we can determine which columns are consistent for i in 1..130; do echo column $i; cat all_column_headers.log | cut -d',' -f$i | sort | uniq -c; done answer: columns 1 to 31 are present in all CSVs. Reduce failure list to first 31 columns cat all_failures_all_smart__column_count_varies.log | cut -d',' -f1-31 > all_failures_smart_columns1to31.log

Smart_9_raw is power-on hours

https://en.wikipedia.org/wiki/S.M.A.R.T.#Known_ATA_S.M.A.R.T._attributes (https://en.wikipedia.org/wiki/S.M.A.R.T.#Known_ATA_S.M.A.R.T._attributes)

In [1]:
```
import pandas
print('pandas',pandas.__version__)
import glob
import pickle
import numpy
import time
import matplotlib.pyplot as plt
```

```
pandas 0.23.4
```

get the headers for the dataframe from a CSV

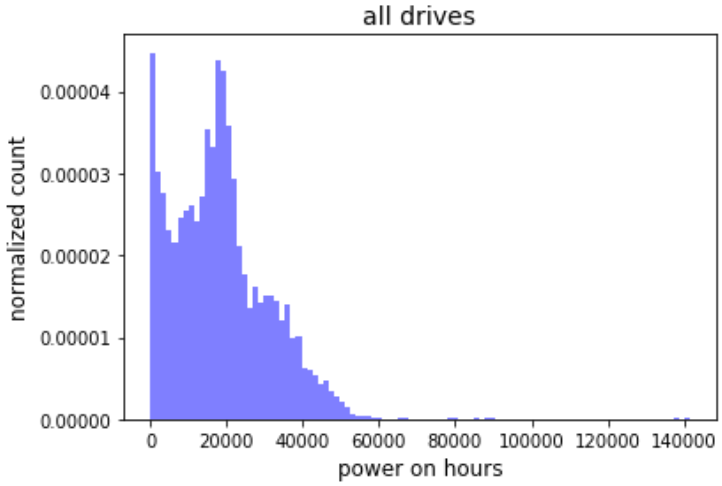
In [2]:
```
df_header_only=pandas.read_csv('zipped_data/data_Q2_2018.zip_folder/2018-04-01.csv',
nrows=3)
#df_header_only.head()
```

In [3]:
```
df = pandas.read_csv('data_synthesized_from_csvs/all_failures_smart_columns1to31.lo
g',header=None)
df.columns=df_header_only.columns[0:31]
df.shape
```

Out[3]:
```
(8743, 31)
```

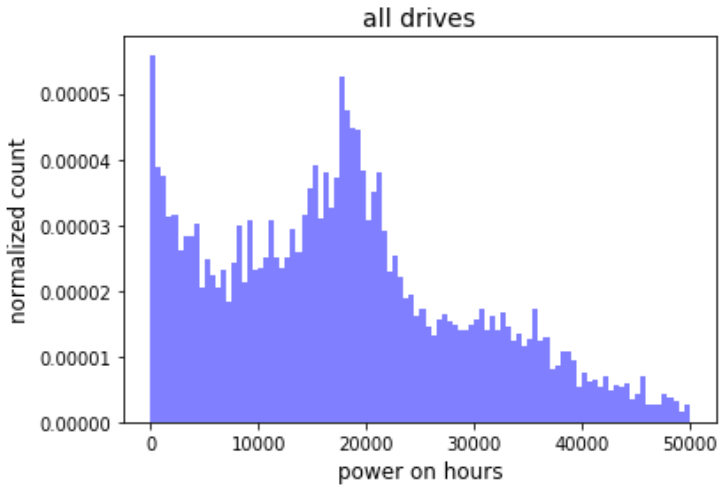
histogram of power-on hours at time of failure

In [4]:
```
n, bins, patches = plt.hist(df['smart_9_raw'].dropna(how='any'),
                            bins=100, facecolor='blue', alpha=0.5,density=True)
plt.xlabel('power on hours',fontsize=12)
plt.ylabel('normalized count',fontsize=12);
plt.title('all drives',fontsize=14);
```

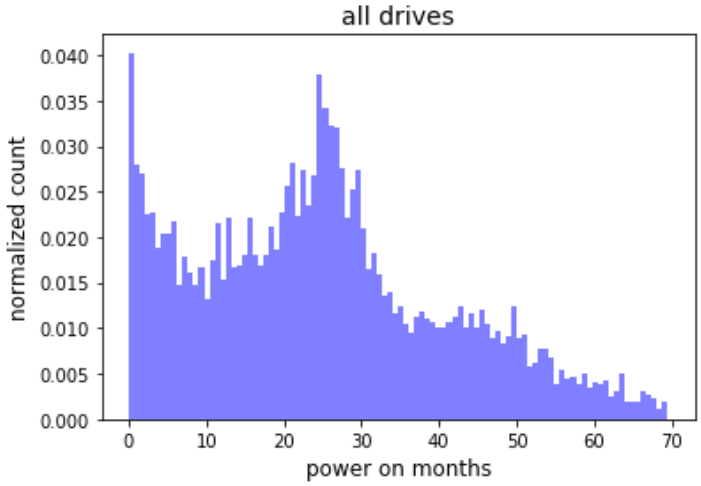


zoom in on relevant lifespans

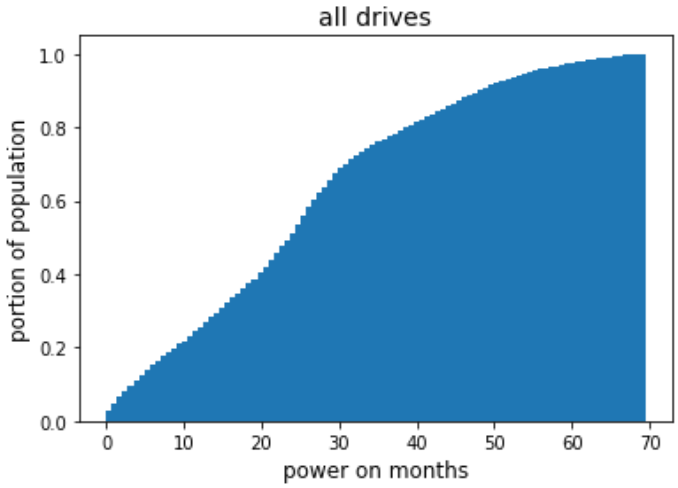
In [5]:
```
n, bins, patches = plt.hist(df[df['smart_9_raw'] < 50000]['smart_9_raw'].dropna(how=
'any'),
                            bins=100, facecolor='blue', alpha=0.5,density=True)
plt.xlabel('power on hours',fontsize=12)
plt.ylabel('normalized count',fontsize=12);
plt.title('all drives',fontsize=14);
```



In [6]:
```
n, bins, patches = plt.hist(df[df['smart_9_raw'] < 50000]['smart_9_raw'].dropna(how=
'any')/24/30,
                            bins=100, facecolor='blue', alpha=0.5,density=True)
plt.xlabel('power on months',fontsize=12)
plt.ylabel('normalized count',fontsize=12);
plt.title('all drives',fontsize=14);
```

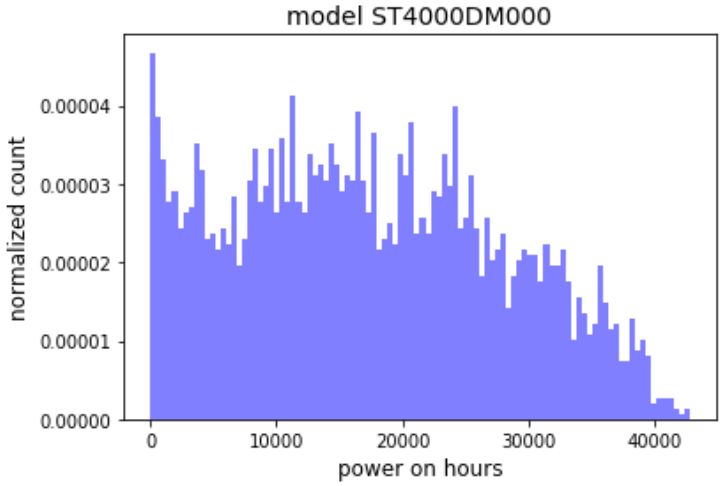


In [7]:
```
n, bins, patches = plt.hist(df[df['smart_9_raw'] < 50000]['smart_9_raw'].dropna(how=
'any')/24/30,
                            bins=100,
                            density=True, cumulative=True) # histtype='step',
plt.xlabel('power on months',fontsize=12)
plt.ylabel('portion of population',fontsize=12);
plt.title('all drives',fontsize=14);
```



Focus on most popular model, ST4000DM000

In [8]:
```
n, bins, patches = plt.hist(df[df['model']=='ST4000DM000']['smart_9_raw'].dropna(how
='any'),
                            bins=100, facecolor='blue', alpha=0.5,density=True)
plt.xlabel('power on hours',fontsize=12)
plt.ylabel('normalized count',fontsize=12);
plt.title('model ST4000DM000',fontsize=14);
```



In [9]:
```
n, bins, patches = plt.hist(df[df['model']=='ST4000DM000']['smart_9_raw'].dropna(how
='any')/24/30,
                            bins=100, facecolor='blue', alpha=0.5,density=True)
plt.xlabel('power on months',fontsize=12)
plt.ylabel('normalized count',fontsize=12);
plt.title('model ST4000DM000',fontsize=14);
```