In [1]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Part 1: Data Selection

1) Data reguarding opioid prescriptions is provided by the \textbf{Center for Medicare and Medicaid Services}, which can be accessed here:

https://data.cms.gov/Medicare-Part-D/Medicare-Part-D-Opioid-Prescriber-Summary-File-201/j2ra-95gh

\underline{Original Data Information}

Provided By: CMS

Contact Email: MedicareProviderData@cms.hhs.gov

Bureau Code: 009:38

Program Code: 009.000

Last Updated: February 8, 2021

Number of Rows: 1,204,935

Number of Columns: 11

In [2]:

```python
op_data = pd.read_csv("op_2021_data.csv")
op_data = op_data.rename(columns = {'NPPES Provider Last Name': 'last_name',
                                    'NPPES Provider First Name': 'first_name',
                                    'NPPES Provider ZIP Code': 'zip_code', 'NPPES Provider
                                    'Specialty Description':'doc_spec',
                                    'Total Claim Count': 'tot_presc_cnt',
                                    'Opioid Claim Count':'op_cnt', 'Opioid Prescribing Rat
                                    'Long-Acting Opioid Claim Count': 'LA_op_cnt',
                                    'Long-Acting Opioid Prescribing Rate': 'LA_op_rate'})
op_data.head()
```

Out[2]:

	NPI	last_name	first_name	zip_code	state	doc_spec	tot_presc_cnt	op_cnt	op_rate	LA_op_c
0	1003000126	ENKESHAFI	ARDALAN	21502.0	MD	Internal Medicine	492	13.0	0.03	N
1	1003000142	KHALIL	RASHID	43623.0	OH	Anesthesiology	1818	891.0	0.49	14
2	1003000167	ESCOBAR	JULIO	89403.0	NV	Dentist	77	NaN	NaN	0
3	1003000282	BLAKEMORE	ROSIE	37243.0	TN	Nurse Practitioner	100	0.0	0.00	0
4	1003000407	GIRARDI	DAVID	15825.0	PA	Family Practice	2766	22.0	0.01	N

\underline{The dataset contains the following values:}

\textbf{NPI:} National Provider Identifier for Doctor Identification.

\textbf{last_name:} Prescribing Doctor's Last Name.

\textbf{first_name:} Prescribing Doctor's First Name.

\textbf{zip_code:} Zip code of the doctor's location.

\textbf{state:} Prescribing Doctor's location.

\textbf{doc_spec:} Specialty of Doctor.

\textbf{tot_presc_cnt:} Total amount of prescriptions by the doctor (inclusive of non-opioids).

\textbf{op_cnt:} Amount of opioid prescriptions by the doctor.

\textbf{op_rate:} Changes in the amount of opioid prescriptions over time by each individual doctor.

\textbf{LA_op_cnt:} Amount of Long-Acting opioid prescriptions by the doctor.

\textbf{LA_op_rate:} Changes in the amount of Long-Acting opioid prescriptions over time by each individual doctor.

Data reguarding average incomes in different area codes is originally provided by the \textbf{Internal Revenue Service (IRS)} , which can be accessed here:

https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-2016-zip-code-data-soi

Data that I will be using has been cleaned and posted for public access by Jon Loyens on data.world, which can be accessed here:

https://data.world/jonloyens/irs-income-by-zip-code

\underline{Original Data Information}

Provided By: Jon Loyens

Contact Address: @jonloyens (twitter)

Last Updated: June 16, 2016

Number of Rows: 27,790

Number of Columns: 11

In [3]:

```
income_data = pd.read_csv("IRSIncomeByZipCode.csv")
income_data = income_data.rename(columns = {'STATE':'state', 'ZIPCODE': 'zip_code',
                                'Number of returns' : 'num_tax_ret',
                                'Adjusted gross income (AGI)': 'zip_agi',
                                'Avg AGI': 'zip_avg_agi',
                                'Number of returns with total income': 'ret_w_total',
                                'Total income amount' : 'sum_zip_income',
                                'Avg total income':'zip_avg_income',
                                'Number of returns with taxable income':'num_ret_taxable',
                                'Taxable income amount': 'taxable_amt',
                                'Avg taxable income':'avg_taxable'})
income_data.head()
```

Out[3]:

	state	zip_code	num_tax_ret	zip_agi	zip_avg_agi	ret_w_total	sum_zip_income	zip_avg_income	num_ret_
0	AL	0	2022380	105089761	51.963410	2022380	106420533	52.621433	1

	state	zip_code	num_tax_ret	zip_agi	zip_avg_agi	ret_w_total	sum_zip_income	zip_avg_income	num_ret_
1	AL	35004	4930	255534	51.832454	4930	258024	52.337525	
2	AL	35005	3300	128387	38.905152	3300	129390	39.209091	
3	AL	35006	1230	58302	47.400000	1230	58585	47.630081	
4	AL	35007	11990	643708	53.687073	11990	651350	54.324437	

\underline{The dataset contains the following values:}

\textbf{state:} The state the zip code is located in.

\textbf{zip_code:} Zip code.

\textbf{num_tax_ret:} The number of tax returns filed in 2016.

\textbf{zip_agi:} Adjusted gross income for residents in a zip.

\textbf{zip_avg_agi:} Average gross income for residents in a zip.

\textbf{ret_w_total:} Number of income tax returns with total income.

\textbf{sum_zip_income:} Summation of all incomes of residents in a zip code.

\textbf{avg_income:} Average income of residents in a zip code, in the thousands. (i.e. 52.3 = 52,300 amount earned, on average, by residents in a shared zip code)

\textbf{num_ret_taxable:} Number of income tax returns with taxable income.

\textbf{taxable_amt:} Summation of the total amount a zip can be taxed.

\textbf{avg_taxable:} Average total taxable income for each area code, in the thousands. (i.e. 40.76 = 40,760 income tax paid by that zip code in 2016)

Part 2: Cleaning

Now we will clean up our dataframe for prescription data and income data by removing unnessicary rows/columns and editing corrupted or non-existant values.

In [4]:

```
#Scrubbing Prescription Data
#removing individual doctor identification, name, and total presciption count (tot_presc_c
#contains non-opioid data).
op_data = op_data[['zip_code', 'state', 'doc_spec', 'op_cnt', 'op_rate', 'LA_op_cnt', 'LA_
#removing doctors who have not prescribed any opioids
op_data = op_data[op_data['op_cnt'] > 0]

#changing zip_code from type float to type int
op_data['zip_code'] = op_data['zip_code'].values.astype(int)
#replacing Nan values in LA_op to 0, as Nan represents long acting opioids were not prescr
op_data['LA_op_cnt'] = op_data['LA_op_cnt'].replace(np.nan, 0)
op_data['LA_op_rate'] = op_data['LA_op_rate'].replace(np.nan, 0)

#Scrubbing income data
#removing unnecessary columns
income_data = income_data[['state', 'zip_code', 'zip_avg_income']]
#removing all non 5 digit zip codes, false data
income_data = income_data[income_data['zip_code'].astype(str).str.len() == 5]
```

Part 3: Merging DataFrames

Now, we will merge our two dataframes, op_data, which contains prescription information as well as ZIP, and income_data, which contains income information as well as ZIP. We will combine on the ZIP datapoint, and data from income will be merged onto the op_data dataframe (op_data will remain stable).

In [5]:

```
op_data = op_data.merge(right = income_data)
op_data
```

Out[5]:

	zip_code	state	doc_spec	op_cnt	op_rate	LA_op_cnt	LA_op_rate	zip_avg_income
0	21502	MD	Internal Medicine	13.0	0.03	0.0	0.00	45.932160
1	21502	MD	Hospitalist	17.0	0.03	0.0	0.00	45.932160
2	21502	MD	Pain Management	994.0	0.71	224.0	0.23	45.932160
3	21502	MD	Nurse Practitioner	106.0	0.14	0.0	0.00	45.932160
4	21502	MD	Physician Assistant	26.0	0.01	0.0	0.00	45.932160
...	...	...	...	...	...	...	...	...
415630	72645	AR	Family Practice	31.0	0.28	0.0	0.00	30.667797
415631	22312	VA	Dentist	12.0	0.11	0.0	0.00	64.716804
415632	67210	KS	General Surgery	17.0	0.28	0.0	0.00	37.551841
415633	95368	CA	Dentist	19.0	0.24	0.0	0.00	51.734295
415634	95623	CA	Dentist	12.0	0.22	0.0	0.00	63.163889

415635 rows × 8 columns

Part 4: EDA

We will now produce visualizations using our finalized dataset, \textbf{op_data}.

\textbf{1)} First, I would like to solve my primary question: Are opioids prescribed more frequently in certain states or zip codes with higher average income?

In [6]:

```
#creating a temp dataframe zip_data to preserve original values when removing outliers and
#removing outliers for greater clarity

zip_df = op_data.groupby('zip_code').mean()

zip_df = zip_df[zip_df['zip_avg_income'] < 200]
zip_df = zip_df[zip_df['op_cnt'] < 1000]



zip_df['income_bin'] = zip_df['zip_avg_income'].values.astype(int)
zip_df.head()
```

Out[6]:

	op_cnt	op_rate	LA_op_cnt	LA_op_rate	zip_avg_income	income_bin
zip_code						
10001	42.121951	0.079268	4.268293	0.043171	155.101676	155
10002	46.020000	0.024200	2.840000	0.043000	46.846786	46
10006	78.333333	0.136667	9.500000	0.028333	181.589407	181

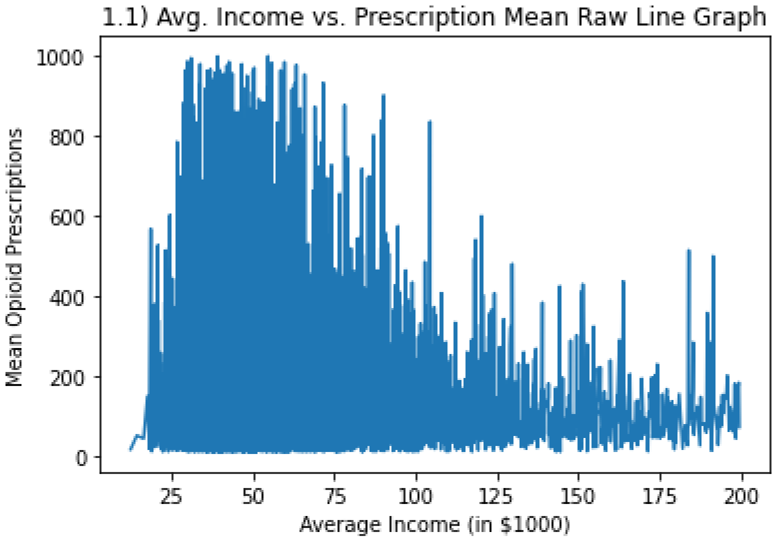
	op_cnt	op_rate	LA_op_cnt	LA_op_rate	zip_avg_income	income_bin
zip_code						
10009	44.833333	0.065833	3.083333	0.014167	72.640410	72
10025	65.891089	0.135248	4.445545	0.069406	133.870043	133

In [7]:

```
sns.lineplot(data = zip_df, x  = zip_df['zip_avg_income'], y = zip_df['op_cnt'])
plt.title('1.1) Avg. Income vs. Prescription Mean Raw Line Graph')
plt.xlabel('Average Income (in $1000)')
plt.ylabel('Mean Opioid Prescriptions')
```

Out[7]:

```
Text(0, 0.5, 'Mean Opioid Prescriptions')
```

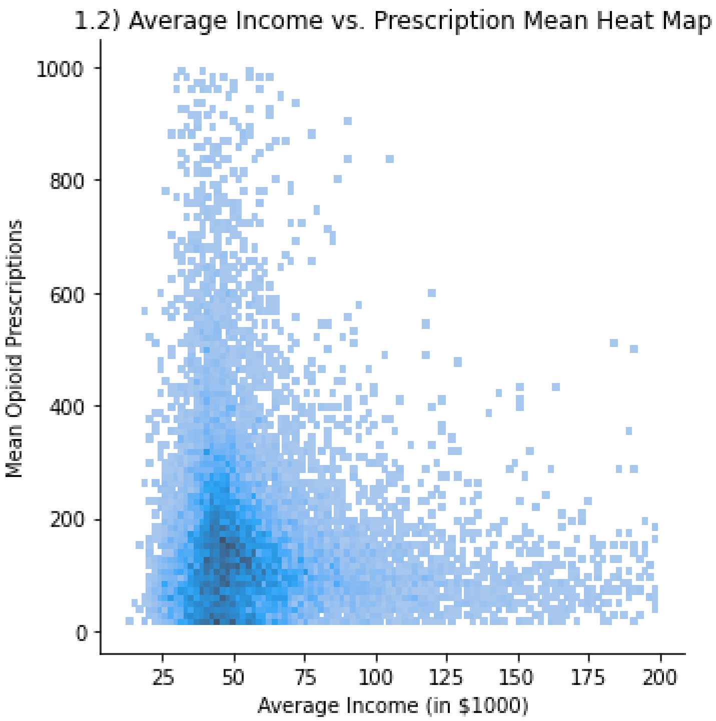


In [8]:

```
sns.displot(zip_df, x = 'zip_avg_income', y = 'op_cnt')

plt.title('1.2) Average Income vs. Prescription Mean Heat Map')
plt.xlabel('Average Income (in $1000)')
plt.ylabel('Mean Opioid Prescriptions')
```

Out[8]:

```
Text(-2.450000000000003, 0.5, 'Mean Opioid Prescriptions')
```



1.2) Average Income vs. Prescription Mean Heat Map

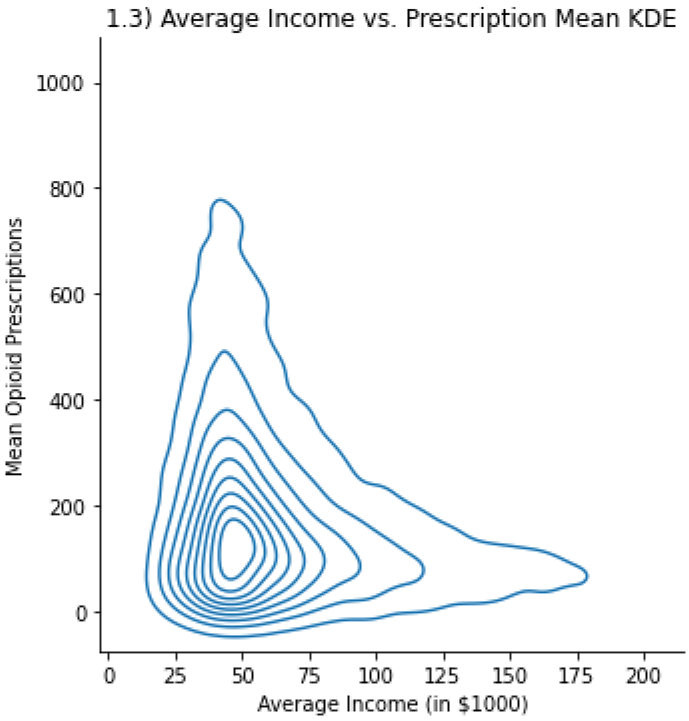
As the heatmap plot above can be difficult to read, we will use a Kernal Density Estimate (KDE) on the bivariate distribution to smooth the x,y obervations with a 2D Gaussian plane. The moreo confined circles show more prescriptions writting for the respective income.

In [9]:

```
sns.displot(zip_df, x = 'zip_avg_income', y = 'op_cnt', kind = 'kde')

plt.title('1.3) Average Income vs. Prescription Mean KDE')
plt.xlabel('Average Income (in $1000)')
plt.ylabel('Mean Opioid Prescriptions')
```

Out[9]:

```
Text(-2.450000000000003, 0.5, 'Mean Opioid Prescriptions')
```



1.3) Average Income vs. Prescription Mean KDE

\textbf{2)} Now we will group our data values by state, using the income of all zips in a state to create a column for each state's average income, labeled \textbf{'state_avg_income'}. Certain states have additional limitations reguarding prescription. For instance, California requires that opioid naive (first time opioid users) must be limited to a 7 day (or less) prescription.

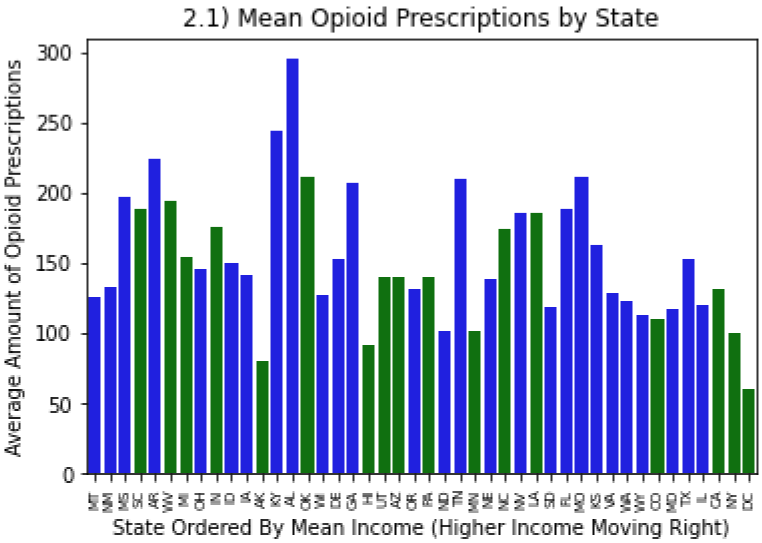
States using additonal limitations reguarding opioids also include: Alaska, Hawaii, Colorado, Utah, Oklahoma, Louisiana, Missouri, Indiana, West Virginia, South Carolina, Pennsylvania, New York, Maine, Arizona, North Carolina, and New Jersy. These states are marked in GREEN.

In [10]:

```
state_df = op_data.groupby('state').mean()
state_df = state_df.rename(columns = {'zip_avg_income': 'state_avg_income'})
#reordering dataframe to go in order from low to high average income states
state_df = state_df.sort_values(by = ['state_avg_income'])

special_states = np.array(['AK', 'HI', 'CO', 'UT', 'OK', 'LA', 'MI', 'IN', 'WV', 'SC', 'PA
                           'NC','AZ', 'MN', 'DC'])

mark_spec_states = ['green' if (x in special_states) else 'blue' for x in state_df.index]
bplot = sns.barplot(data = state_df, x = state_df.index, y = 'op_cnt', palette = mark_spec

plt.title('2.1) Mean Opioid Prescriptions by State')
plt.xlabel('State Ordered By Mean Income (Higher Income Moving Right)')
plt.ylabel('Average Amount of Opioid Prescriptions')
bplot.set_xticklabels(bplot.get_xticklabels(),rotation = 90, size = 7)
```

Out[10]:

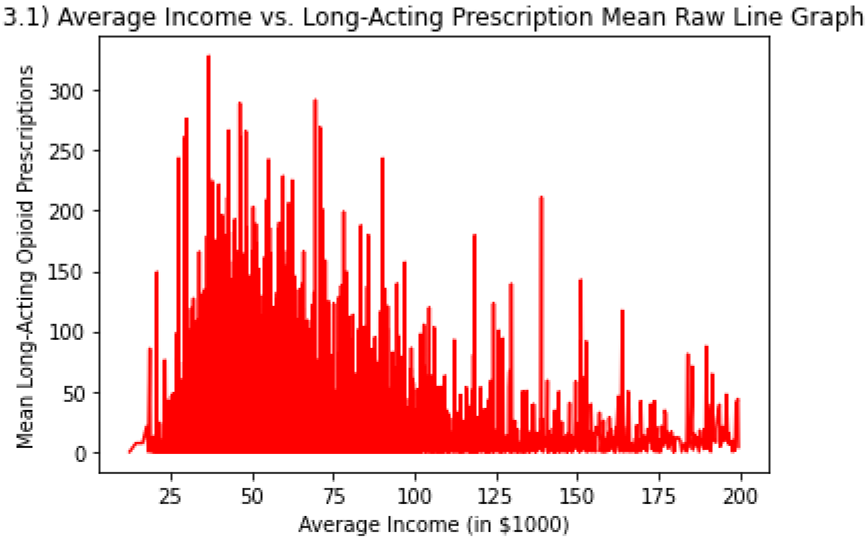
```
[Text(0, 0, 'MT'),
 Text(1, 0, 'NM'),
 Text(2, 0, 'MS'),
 Text(3, 0, 'SC'),
 Text(4, 0, 'AR'),
 Text(5, 0, 'WV'),
 Text(6, 0, 'MI'),
 Text(7, 0, 'OH'),
 Text(8, 0, 'IN'),
 Text(9, 0, 'ID'),
 Text(10, 0, 'IA'),
 Text(11, 0, 'AK'),
 Text(12, 0, 'KY'),
 Text(13, 0, 'AL'),
 Text(14, 0, 'OK'),
 Text(15, 0, 'WI'),
 Text(16, 0, 'DE'),
 Text(17, 0, 'GA'),
 Text(18, 0, 'HI'),
 Text(19, 0, 'UT'),
 Text(20, 0, 'AZ'),
 Text(21, 0, 'OR'),
 Text(22, 0, 'PA'),
 Text(23, 0, 'ND'),
 Text(24, 0, 'TN'),
 Text(25, 0, 'MN'),
 Text(26, 0, 'NE'),
 Text(27, 0, 'NC'),
 Text(28, 0, 'NV'),
 Text(29, 0, 'LA'),
 Text(30, 0, 'SD'),
 Text(31, 0, 'FL'),
 Text(32, 0, 'MO'),
 Text(33, 0, 'KS'),
 Text(34, 0, 'VA'),
 Text(35, 0, 'WA'),
 Text(36, 0, 'WY'),
 Text(37, 0, 'CO'),
 Text(38, 0, 'MD'),
 Text(39, 0, 'TX'),
 Text(40, 0, 'IL'),
 Text(41, 0, 'CA'),
 Text(42, 0, 'NY'),
 Text(43, 0, 'DC')]
```



\textbf{3)} Additionally, I want to also find out if long acting opioid treatment therapy is used more often in higher income areas.

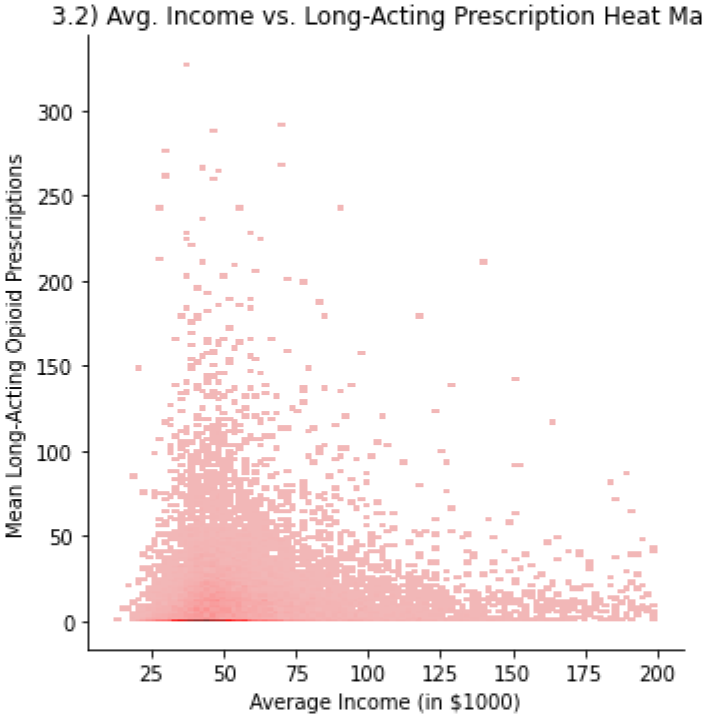
In [11]:
```
sns.lineplot(data = zip_df, x  = zip_df['zip_avg_income'], y = zip_df['LA_op_cnt'], color

plt.title('3.1) Average Income vs. Long-Acting Prescription Mean Raw Line Graph')
plt.xlabel('Average Income (in $1000)')
plt.ylabel('Mean Long-Acting Opioid Prescriptions')
```

Out[11]:
```
Text(0, 0.5, 'Mean Long-Acting Opioid Prescriptions')
```



In [12]:
```
sns.displot(zip_df, x = 'zip_avg_income', y = 'LA_op_cnt', color = 'red')

plt.title('3.2) Avg. Income vs. Long-Acting Prescription Heat Map')
plt.xlabel('Average Income (in $1000)')
plt.ylabel('Mean Long-Acting Opioid Prescriptions')
```

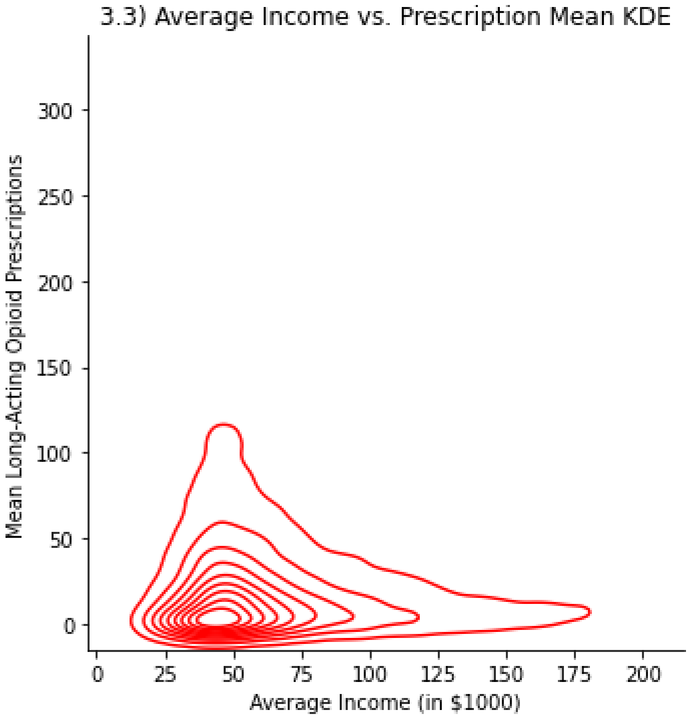
Out[12]:
```
Text(3.674999999999997, 0.5, 'Mean Long-Acting Opioid Prescriptions')
```


3.2) Avg. Income vs. Long-Acting Prescription Heat Map

Once again, as our heatmap can be difficult to read, we will once again create a KDE.

In [13]:
```
sns.displot(zip_df, x = 'zip_avg_income', y = 'LA_op_cnt', kind = 'kde', color = 'red')
plt.title('3.3) Average Income vs. Prescription Mean KDE')
plt.xlabel('Average Income (in $1000)')
plt.ylabel('Mean Long-Acting Opioid Prescriptions')
```

Out[13]:
```
Text(3.674999999999997, 0.5, 'Mean Long-Acting Opioid Prescriptions')
```

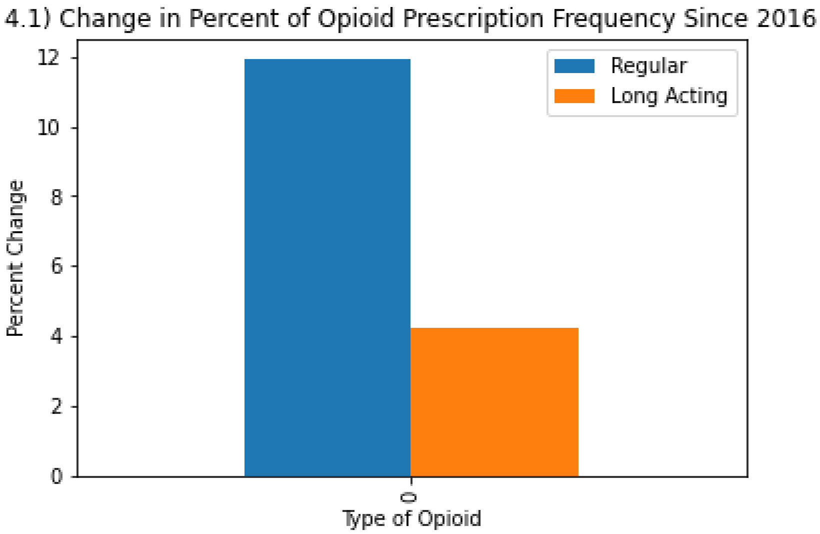

3.3) Average Income vs. Prescription Mean KDE

\textbf{4)} Finally, I would like to see the change in prescriber rates for both regular and Long-Acting opioid prescriptions over the last 5 years. Our DataSet has 2 columns that hold this information, \textbf{op_rate} and \textbf{LA_op_rate}, which show percent changes over the course of the last 5 years for each individual doctor.

In [17]:
```
zip_df['op_rate'].mean()
time_df = pd.DataFrame()
time_df['Regular'] = [zip_df['op_rate'].mean() * 100]
```

```
time_df['Long Acting'] = [zip_df['LA_op_rate'].mean() * 100]
time_df.plot.bar()
plt.title('4.1) Change in Percent of Opioid Prescription Frequency Since 2016')
plt.xlabel('Type of Opioid')
plt.ylabel('Percent Change')
print('Percent Change for Regular Acting Opiods: ', time_df['Regular'][0])
print('Percent Change for Long Acting Opiods: ', time_df['Long Acting'][0])
```

```
Percent Change for Regular Acting Opiods:  11.908343992174487
Percent Change for Long Acting Opiods:  4.244034761724507
```



Conclusion

A: Opioids appear to be less frequently prescribed in regions with a higher average income, as shown by the stretching in fig.1.3 as well as the heat map (fig.1.2). The mean prescription density spreads horizontally and drops steeply and significantly after region incomes of USD 50,000. Thus, we can see as income increases, opioid prescription frequency decreases. There is also a decrease in opioid prescribing for income areas below USD 25,000. One possible explanation for this could be an inability to afford proper healthcare and be able to see a doctor to prescribed opioids- even if they may really need them.

B: From looking at graph 2.1, cannot definitively conclude that states with higher average incomes have lower frequency of opioid prescriptions. However, it can be observed that states placing additional, more stringent requirements on prescriptions have distinctive decreases in mean opioid prescriptions.

C: Although there is similar decrease in frequency as income increases between regular and Long-Acting opioids, it is notable that there is much quicker decreases for short acting. Thus, to some extent, there can be a greater frequency of prescribing LA opioids instead for higher income areas, even though the average amount of opioids prescribed still remains lower for higher income areas. A possible explanation for this is that those in higher income areas may live busier life, and thus doctors may prescribe Long-Acting to prevent skipped or forgotten doses.

D: There has been a 11.91% increase in regular acting prescriptions and 4.24% increase in Long-Acting prescriptions for opioids over the last 5 years.

In [ ]: