Analysis of Top Ranked Colleges in the United States

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:
```
df = pd.read_csv('[redacted]
df.head(3)
```

Out[3]:

	Rank	Name	City	State	Public/Private	Undergraduate Population	Student Population	Net Price	Aver G
0	1.0	Harvard University	Cambridge	MA	Private	13844.0	31120.0	14327.0	498
1	2.0	Stanford University	Stanford	CA	Private	8402.0	17534.0	13261.0	501
2	3.0	Yale University	New Haven	CT	Private	6483.0	12974.0	18627.0	508

Variable Creation

Test Scores

Looking at the columns from the dataframe, I noticed that there was a lower and upper value for both the student population's SAT and ACT scores, but not an average, so I wanted to create an average variable myself. Note: This average is not the average score of the student population, but the average score between the highest and lowest scorers amonst the population.

Public/Private

The variable is currently contained as a string, which isn't very useful for data analysis, so I decided to turn it into a binary variable where '1' were all public schools, and '0' were all private.

Undergraduate Percentage

The percentage of the student population enrolled in an undergraduate program

Test Difference

The difference between the highest and lowest test scores

Post-UG Population

The student population enrolled beyond an undergraduate education.

Post-UG Percentage

Percentage of the student population enrolled after obtaining a Bachelor's degree.

In [4]:
```
df['SAT Average']=df['SAT Lower']/2+df['SAT Upper']/2
df['ACT Average']=df['ACT Lower']/2+df['ACT Upper']/2

df.head(3)
```

Out[4]:

	Rank	Name	City	State	Public/Private	Undergraduate Population	Student Population	Net Price	Aver G
0	1.0	Harvard University	Cambridge	MA	Private	13844.0	31120.0	14327.0	498
1	2.0	Stanford University	Stanford	CA	Private	8402.0	17534.0	13261.0	501
2	3.0	Yale University	New Haven	CT	Private	6483.0	12974.0	18627.0	508

In [5]:
```
dummy=pd.get_dummies(df['Public/Private'], drop_first=True)
df=pd.concat([df, dummy], axis=1)
df=df.drop(['Public/Private', 'Website'], axis=1)
df.head(3)
```

Out[5]:

	Rank	Name	City	State	Undergraduate Population	Student Population	Net Price	Average Grant Aid	Total Annual Cost
0	1.0	Harvard University	Cambridge	MA	13844.0	31120.0	14327.0	49870.0	69600.0
1	2.0	Stanford University	Stanford	CA	8402.0	17534.0	13261.0	50134.0	69109.0
2	3.0	Yale University	New Haven	CT	6483.0	12974.0	18627.0	50897.0	71290.0

In [6]:

```
df['Undergraduate Percentage'] = df['Undergraduate Population']/ df['Student
df['ACT Difference'] = df['ACT Average']-20.6
df['SAT Difference'] = df['SAT Average']-1051
df['Post-UG Population'] = df['Student Population'] - df['Undergraduate Popul
df['Post-UG Percentage'] = df['Post-UG Population'] / df['Student Population'
df.head(3)
```

Out[6]:

	Rank	Name	City	State	Undergraduate Population	Student Population	Net Price	Average Grant Aid	Total Annual Cost
0	1.0	Harvard University	Cambridge	MA	13844.0	31120.0	14327.0	49870.0	69600.0
1	2.0	Stanford University	Stanford	CA	8402.0	17534.0	13261.0	50134.0	69109.0
2	3.0	Yale University	New Haven	CT	6483.0	12974.0	18627.0	50897.0	71290.0

3 rows × 23 columns

Gathering Summary Statistics on Data

In [7]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 650 entries, 0 to 649
Data columns (total 23 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   Rank                       650 non-null    float64
 1   Name                       650 non-null    object 
 2   City                       647 non-null    object 
 3   State                      650 non-null    object 
 4   Undergraduate Population   650 non-null    float64
 5   Student Population         650 non-null    float64
 6   Net Price                  648 non-null    float64
 7   Average Grant Aid          646 non-null    float64
 8   Total Annual Cost          650 non-null    float64
 9   Alumni Salary              635 non-null    float64
 10  Acceptance Rate            648 non-null    float64
 11  SAT Lower                  551 non-null    float64
 12  SAT Upper                  551 non-null    float64
 13  ACT Lower                  553 non-null    float64
 14  ACT Upper                  553 non-null    float64
 15  SAT Average                551 non-null    float64
 16  ACT Average                553 non-null    float64
 17  Public                     650 non-null    uint8  
 18  Undergraduate Percentage   650 non-null    float64
 19  ACT Difference             553 non-null    float64
 20  SAT Difference             551 non-null    float64
 21  Post-UG Population         650 non-null    float64
 22  Post-UG Percentage         650 non-null    float64
dtypes: float64(19), object(3), uint8(1)
memory usage: 112.5+ KB
```

As the table shows, there are null values in my data. For example, about 15% of the SAT variables are null values. Null values can be troublesome for machine learning, so I shouvld do something about them. The two simplest ways are to remove any record containing a null value, or estimating the null values. By deleting the values, I'd be effectively cutting down my available data by around 1/5th, meaning the data's predictive capability would lessen. On the other hand, estimating values in place of the nulls might not be accurate, and so can also harm the predictive capabilities of the model based on how off they are.

Later on, I will be trying out both methods to try and maximize my models' predictive capabilities.

In [8]:
```
df.describe()
```

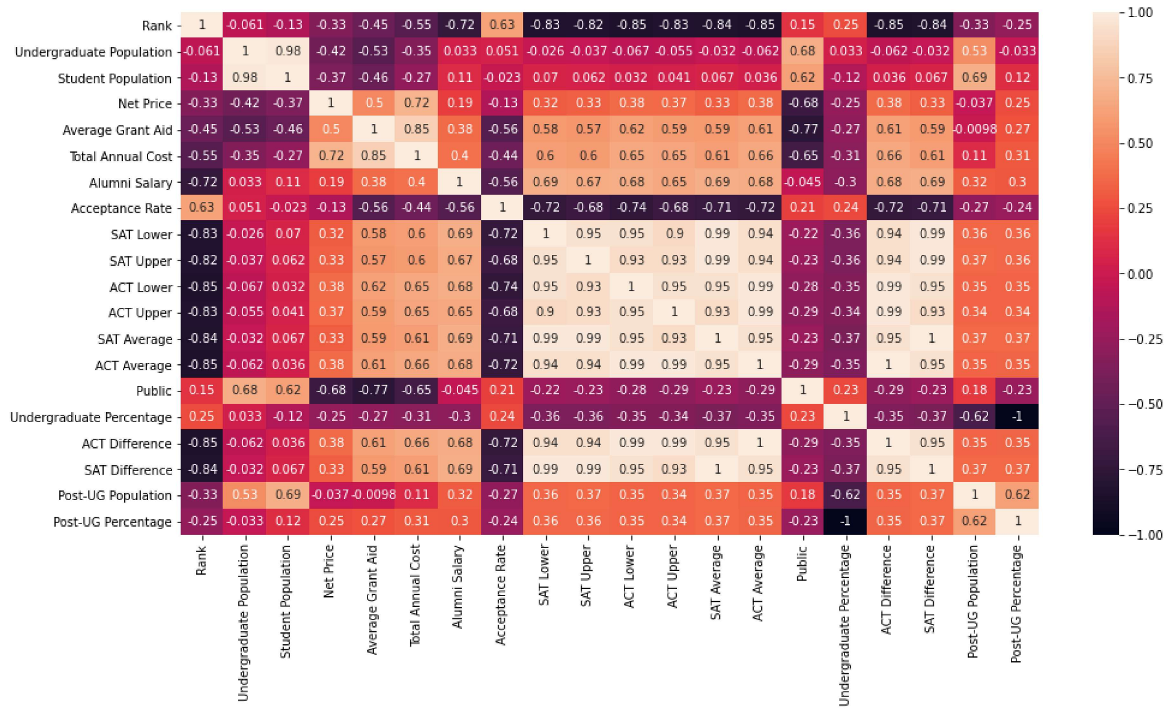
Out[8]:

	Rank	Undergraduate Population	Student Population	Net Price	Average Grant Aid	Total Annual Cost	Al
count	650.00000	650.000000	650.000000	648.000000	646.000000	650.000000	
mean	325.50000	10002.692308	12022.290769	22336.947531	20031.208978	50330.175385	98
std	187.78312	11162.172430	13175.091581	8269.912032	11175.869976	13223.055038	14
min	1.00000	185.000000	386.000000	0.000000	2975.000000	0.000000	70
25%	163.25000	2020.250000	2240.750000	16410.000000	9288.250000	39917.000000	88
50%	325.50000	4503.000000	6269.000000	21989.000000	19605.000000	50265.000000	96
75%	487.75000	15657.000000	17788.000000	27580.500000	27474.500000	60771.750000	105
max	650.00000	65100.000000	75044.000000	47270.000000	50897.000000	75735.000000	158

The first thing that jumps out to me is how varied the data is. For instance the Public column is a binary variable using zero and one, while the Student Population column has a range between 386 and 75044. Because of this, any machine learning models will place more weight to the variables with the larger values. I should standardize and scale the data so that everything will be weighted equally in the machine learning models.

In [9]:
```python
df_corr = df.corr()
plt.figure(figsize=(16,8))
sns.heatmap(df_corr, annot=True)
```

Out[9]:
```
<AxesSubplot:>
```



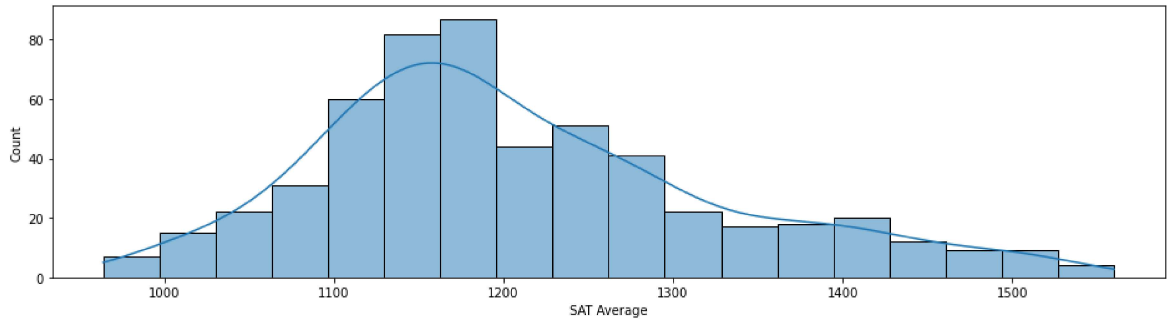
In [10]:
```python
df_corr["Rank"].sort_values(ascending=False)
```

Out[10]:
```
Rank                         1.000000
Acceptance Rate              0.628110
Undergraduate Percentage     0.250042
Public                       0.147599
Undergraduate Population    -0.060859
Student Population          -0.133249
Post-UG Percentage          -0.250042
Net Price                   -0.329445
Post-UG Population          -0.329503
Average Grant Aid           -0.445638
Total Annual Cost           -0.552349
Alumni Salary               -0.721772
SAT Upper                   -0.822319
ACT Upper                   -0.830561
SAT Lower                   -0.834263
SAT Average                 -0.839476
SAT Difference              -0.839476
ACT Lower                   -0.849047
ACT Difference              -0.851101
ACT Average                 -0.851101
Name: Rank, dtype: float64
```

These correlations are what one would expect at first glance. Public schools with a more inclusive acceptance rate and a large portion of their population being undergraduate tend to be lowly ranked, while the higher test scores and alumni salary tend to go to higher ranked colleges.

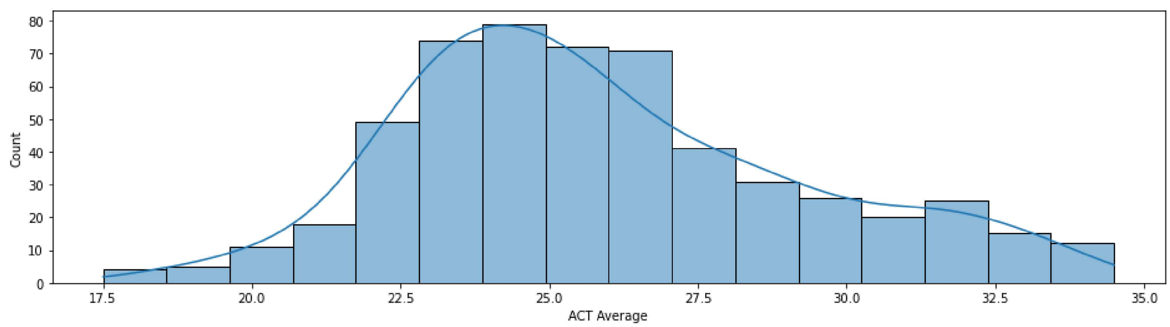
In [11]:
```
plt.figure(figsize=(16,4))
sns.histplot(df['SAT Average'], kde=True)
#average is 1051
```

Out[11]: <AxesSubplot:xlabel='SAT Average', ylabel='Count'>



In [12]:
```
plt.figure(figsize=(16,4))
sns.histplot(df['ACT Average'], kde=True)
#average is 20.6
```

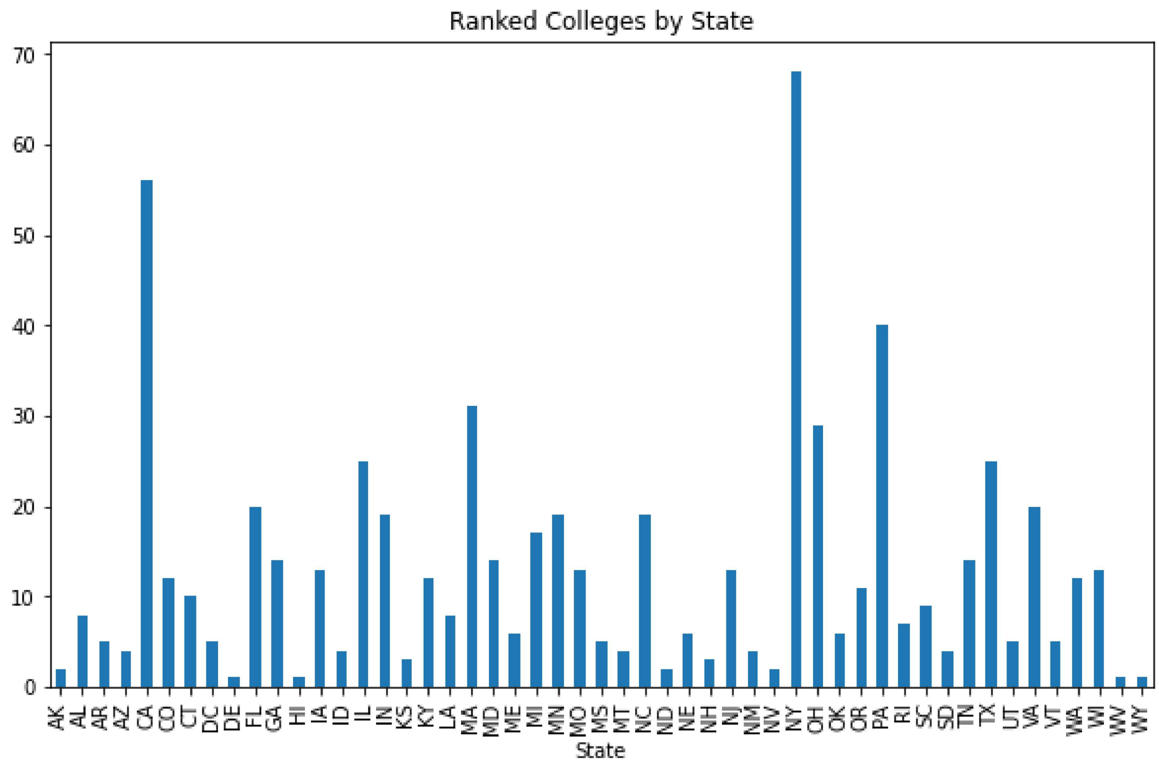
Out[12]: <AxesSubplot:xlabel='ACT Average', ylabel='Count'>



As both graphs show, the average test score - which is the difference between the highest scoring studen and lowest scoring student - are usually higher than the average test scores of the population. This is a bit of comparing apples to oranges due to the different ways average scores are calculated here, but this does show that the colleges in this dataset typically go after higher scoring students.

In [13]:

```
state_rank=df['Rank'].groupby([df['State']]).count()
state_rank.plot(kind='bar', title = 'Ranked Colleges by State', figsize = (10
```



In [14]:

```
census = pd.read_excel[redacted]
census.head(3)
```

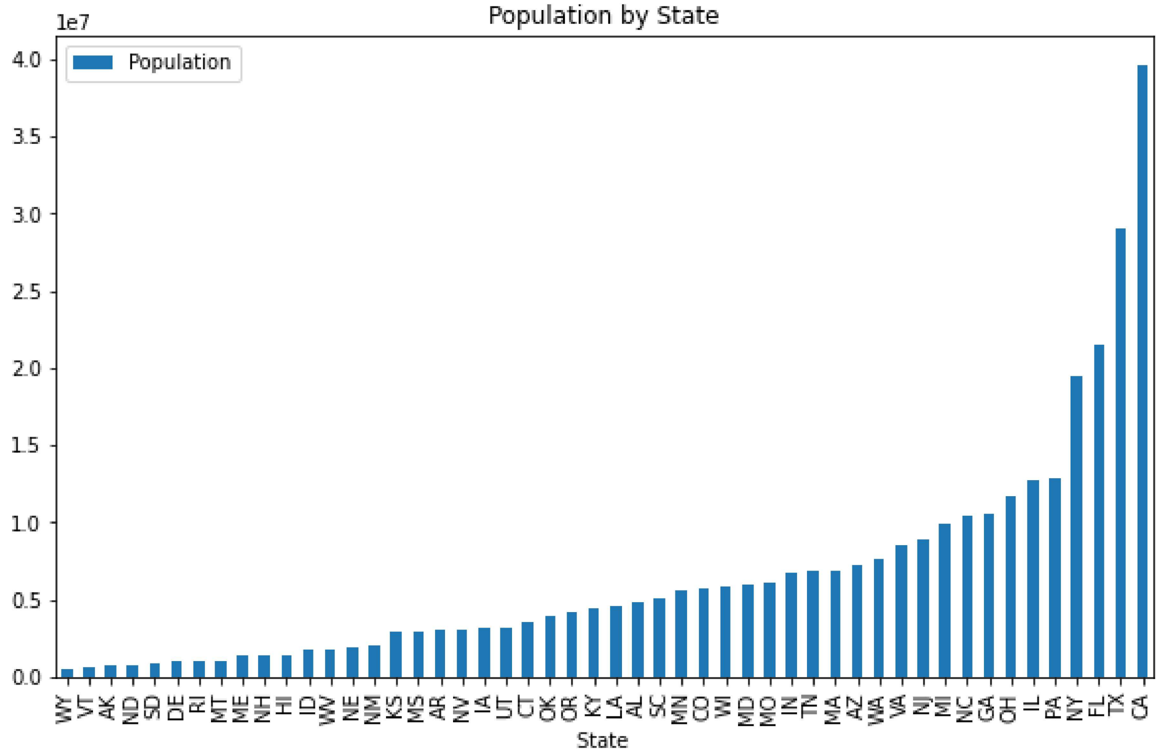
Out[14]:

	Population
State	
AL	4903185
AK	731545
AZ	7278717

In [15]:
```
census_sorted= census.sort_values('Population')
state_rank_sorted = state_rank.sort_values()
```

In [16]:
```
census_sorted.plot(kind='bar', title = 'Population by State', figsize = (10,6
```

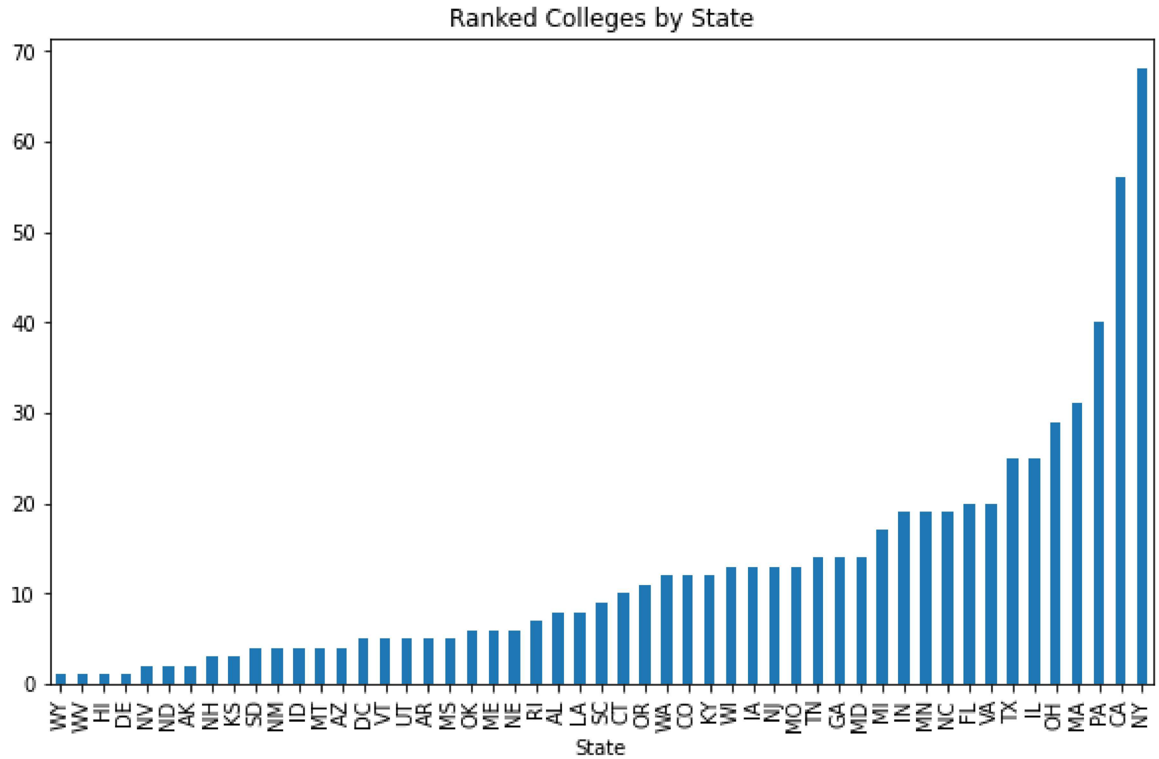
Out[16]: <AxesSubplot:title={'center':'Population by State'}, xlabel='State '>



In [17]:

```
state_rank_sorted.plot(kind='bar', title = 'Ranked Colleges by State', figsiz
```

Out[17]: <AxesSubplot:title={'center':'Ranked Colleges by State'}, xlabel='State'>



As to be expected, the amount of ranked colleges in a state almost exactly follows the population distribution of the states. One notable exception to this is Texas, which is the second highest state by population, but only the seventh highest in terms of ranked universities. In fact, it should have around twice as many ranked universities as it does currently.

Building a Model to Predict College Rankings

In [18]:
```
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
```

Step 1

Step one of my machine learning process is preparing the data to be more useful to the algorithms. In this instance, that means removing all the columns made up of strings, as well as separating the predicted variable from the explainer variables. Furthermore, I'll be dividing the data between a train set and a test set. As the names imply, a training set is what the machine learning models are initially built off of, while the test set is used to test the model's accuracy.

One does not want to use a training set for both training and testing as one could accidentally overfitt the model to the data, meaning, while the model is useful for the specific data used, if any more data is brought in, the model will become much more inaccurate than a model tested with a separate test set of data.

In [19]:
```
df=df.drop(['Name', 'City', 'State'], axis = 1)
df_goal=df['Rank'].copy()
df2=df.drop('Rank', axis=1)
df_train, df_test, goal_train, goal_test = train_test_split(df2, df_goal, tes
```

In [20]:
```
df_train.head(3)
```

Out[20]:

	Undergraduate Population	Student Population	Net Price	Average Grant Aid	Total Annual Cost	Alumni Salary	Acceptance Rate	SAT Lower	S Up
522	22386.0	24375.0	15368.0	7270.0	43444.0	89900.0	86.0	980.0	12(
178	2367.0	2535.0	31014.0	25282.0	65330.0	101900.0	48.0	1140.0	134
260	29777.0	30896.0	20493.0	8263.0	44706.0	104800.0	79.0	1070.0	13(

To prepare the data more, I will also be standardizing the data so that the whole set will have similar deviations. I will also be implementing an imputer to fill in the nulls values in the data with an estimate of what they could be based on the column's median value. I am doing this to save as much of the data as possible, but later I will make a regressor model without the imputer to see how it compares.

In [21]:
```
standardscaler = StandardScaler()
imputer = SimpleImputer(strategy='median')
pipe = Pipeline([('std', standardscaler), ('imputer', imputer)])
pipe.fit(df_train, goal_train)
df_train2 = pipe.transform(df_train)
df_test2 = pipe.transform(df_test)
```

First Model: K-Nearest Neighbors

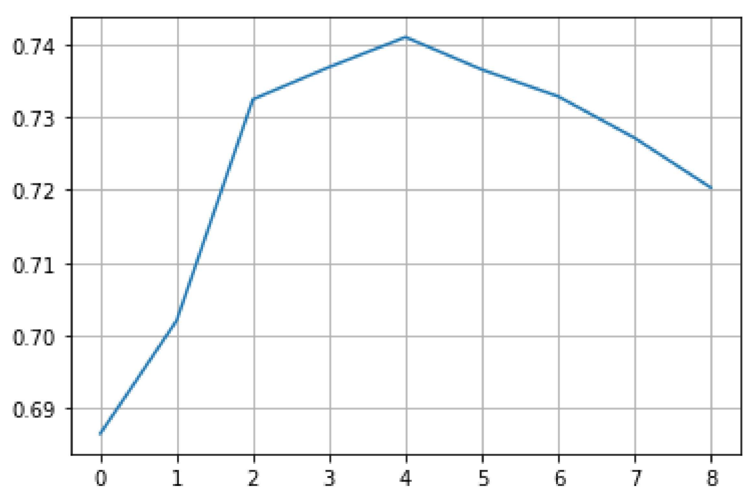
The first model we will run is a KNN model. This model is one of the simplest machine learning models to run, meaning it also takes much less resources on the system than a more complex model. Typically one should use the simplest model first in order to save on resources. In the case of K-Nearest Neighbors, it takes the given records and compares them to the records with the variables closest to them. So if I wanted to know what rank a public university with an acceptance rate of 70% and a net price of $18,000, the model will look at the closest public universities with a similar acceptance rate and net price.

Every model will be judged by two criteria: the RMSE, or root mean squared error, and the cross validation accuracy score. RMSE refers to the absolute value of the error in a predicted value. So if the model predicts a college will be ranked 4th, but in reality it was ranked 2nd, then the RMSE of the prediction would be two. Cross validation is typically used when the data is rather limites or as a way to protect against overfitting the data. Basically the training set will be split up many more times and iterations of the machine learning algorithm will be fitted and tested against the partitions. You can then average out the accuracy of the partitions, and get an overall accuracy score for the predictions.

In [22]:
```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score
```

In [23]:
```
n_neighbors =list(range(1, 10))
accuracy = []
for neighbor in n_neighbors:
    clf = KNeighborsRegressor(n_neighbors = neighbor)
    clf.fit(df_train2, goal_train)
    score = clf.score(df_test2, goal_test)
    accuracy.append(score)
plt.grid(True)
plt.plot(accuracy)
```

Out[23]:
```
[<matplotlib.lines.Line2D at 0x1f053681e50>]
```



Many machine learning models allow for parameter tuning to get the best predictive results. In the case of K-Nearest Neighbors, one can choose the amount of neighbors closest to the college being predicted. One might think that more is always better, but adding more neighbors takes more system resources and can hurt the predictive capabilities of the model. In the case of the above, we can see that the model is most accurate when limited to four nearest neighbors.

In [24]:
```
knn = KNeighborsRegressor(n_neighbors = 4)
knn.fit(df_train2, goal_train)
knn_predict = knn.predict(df_test2)
knn_mse = np.power(goal_test - knn_predict, 2).mean()
```

In [25]:
```
knn_mse
```

Out[25]:
```
9319.088662790698
```

In [26]:
```
mean_squared_error(goal_test, knn_predict)
```

Out[26]:
```
9319.088662790698
```

In [27]:
```
knn_rmse= knn_mse ** .5
knn_rmse
```

Out[27]:
```
96.53542698300298
```

The accuracy score given while doing parameter tuning was not a robust score. It was good for determining the best number of parameters to use, but it is likely off by at least a little bit due to only running the model once on a select subset of the data. Therefore I'll be using cross validation to get a more accurate score.

In [28]:
```
knn_scores = cross_val_score(knn, df_test2, goal_test, cv=10)
knn_scores
```

Out[28]:
```
array([0.794885  , 0.71838554, 0.8986766 , 0.81744243, 0.7089424 ,
       0.68471291, 0.59426826, 0.76292426, 0.63861639, 0.77691769])
```

In [29]:
```
knn_scores.mean()
```

Out[29]:
```
0.7395771478536421
```

With an RMSE of 96.5 and an accuracy score of 73.9%, this model isn't a great predictor of a college's rank. It's accuracy score is respectable, but the RMSE of 96.5 means that it won't predict much. There is a huge difference in a college in the top 10 and a college in the top 100, yet the model is likely to miss the correct ranking of a college by about the same amount. We will be moving on to other models to try and get a effective model.

Second Model: Linear Regression

The second model will be a linear regression. Linear regressions are also a simpler type of regression, but, depending on the variables involved, they are generally more complex than KNN. I'll be building a linear regression model using two methods. This is because, while Sci-Kit Learn's regressions allow a user to do many things, they don't allow you to analyse individual variables, something offered by Statemodels. So I'll be using both.

In [30]:
```
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
reg = LinearRegression()
reg.fit(df_train2, goal_train)
reg_predict = reg.predict(df_test2)
```

In [31]:
```
reg_mse = np.power(goal_test - reg_predict, 2).mean()
reg_mse
```

Out[31]:
```
10302.234400465317
```

In [32]:
```
mean_squared_error(goal_test, reg_predict)
```

Out[32]:
```
10302.234400465317
```

In [33]:
```
reg_rmse= reg_mse **.5
reg_rmse
```

Out[33]:
```
101.49992315497248
```

In [34]:
```
reg_scores = cross_val_score(reg, df_test2, goal_test, cv=10)
reg_scores
```

Out[34]:
```
array([0.74019212, 0.64185176, 0.80766255, 0.77701872, 0.73228213,
       0.65909261, 0.6692306 , 0.72233914, 0.73605185, 0.74614342])
```

In [35]:
```
reg_scores.mean()
```

Out[35]:
```
0.7231864884213678
```

In [36]:
```
x=sm.add_constant(df_train2)
model = sm.OLS(goal_train, x)
results = model.fit()
results.summary()
```

Out[36]:

OLS Regression Results

Dep. Variable:	Rank	**R-squared:**	0.753
Model:	OLS	**Adj. R-squared:**	0.745
Method:	Least Squares	**F-statistic:**	91.41
Date:	Mon, 13 Sep 2021	**Prob (F-statistic):**	7.74e-118
Time:	20:49:51	**Log-Likelihood:**	-2588.4
No. Observations:	435	**AIC:**	5207.
Df Residuals:	420	**BIC:**	5268.
Df Model:	14		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	328.7755	5.059	64.991	0.000	318.832	338.719
x1	-20.4626	5.775	-3.544	0.000	-31.813	-9.112
x2	-15.3993	3.476	-4.430	0.000	-22.232	-8.566
x3	-22.9348	9.319	-2.461	0.014	-41.252	-4.618
x4	26.9552	14.075	1.915	0.056	-0.710	54.621
x5	-47.8183	12.510	-3.822	0.000	-72.408	-23.228
x6	-42.5044	6.724	-6.322	0.000	-55.720	-29.288
x7	29.3555	6.753	4.347	0.000	16.083	42.629
x8	38.5810	169.204	0.228	0.820	-294.010	371.172
x9	26.0582	149.456	0.174	0.862	-267.716	319.832
x10	-15.5589	18.712	-0.831	0.406	-52.340	21.222
x11	-19.7339	19.315	-1.022	0.308	-57.699	18.231
x12	-45.1689	157.650	-0.287	0.775	-355.050	264.712
x13	-17.6337	4.215	-4.183	0.000	-25.919	-9.348
x14	1.7050	11.227	0.152	0.879	-20.363	23.772
x15	-5.5583	3.489	-1.593	0.112	-12.416	1.300
x16	-17.6337	4.215	-4.183	0.000	-25.919	-9.348
x17	-45.1689	157.650	-0.287	0.775	-355.050	264.712
x18	7.9363	9.090	0.873	0.383	-9.931	25.803
x19	5.5583	3.489	1.593	0.112	-1.300	12.416

Omnibus:	1.895	**Durbin-Watson:**	1.906

Prob(Omnibus):	0.388	**Jarque-Bera (JB):**	1.718
Skew:	-0.081	**Prob(JB):**	0.424
Kurtosis:	3.261	**Cond. No.**	1.61e+16

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.52e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Third Model: Random Forest Regressor

This model is by far the most complex of the models used. Similar to how cross validation treats training data, random forest regressors takes a decision tree and runs multiple iterations against the data, averaging out the iterations. It's a great overall model and tends to work better on more complex datasets.

In [37]:
```
from sklearn.ensemble import RandomForestRegressor
forest=RandomForestRegressor(random_state=42)
forest.fit(df_train2, goal_train)
forest_predict = forest.predict(df_test2)
forest_mse = np.power(goal_test - forest_predict, 2).mean()
forest_mse
```

Out[37]:
```
6960.33954604651
```

In [38]:
```
forest_rmse= forest_mse **.5
forest_rmse
```

Out[38]:
```
83.42864943199375
```

In [39]:
```
forest_scores = cross_val_score(forest, df_test2, goal_test, cv=10)
forest_scores
```

Out[39]:
```
array([0.86632698, 0.75866635, 0.83249986, 0.8694084 , 0.69275768,
       0.75625868, 0.74860723, 0.81315518, 0.83219168, 0.8311133 ])
```

In [40]:
```
forest_scores.mean()
```

Out[40]:
```
0.8000985332657431
```

With an RMSE of 83.4, over ten digits under the RMSE of the KNN model, and an accuracy of 80% - 6% higher than the accuracy of the KNN model, this model performs better against the data to a sizable degree compared to the other models.

That being said, a standard error in predicting a rank being 83.4 digits is not a good predictor. The most likely reason for this being that the parameter variables given are not themselves a strong enough predictor for a college rank, suggesting that more information is used to determine a college's ranking than just the ones given.

No Impute

The goal of the following analysis is to test the best predictive model from our previous selections and test it against a copy of the dataset where I removed all the records with null values instead of using estimated values.

For this test I will just be using the random forest regressor. While normally it'd be worth testing more models, since the predicted and predictor variables aren't changing outside of the null values, it's more efficient to just bring the best predictive model over.

In [41]:
```
df3=df.dropna()
df3_goal=df3['Rank'].copy()
df3=df3.drop(['Rank'], axis=1)
```

In [42]:
```
df_train3, df_test3, goal_train3, goal_test3 = train_test_split(df3, df3_goal
pipe2 = Pipeline([('std', standardscaler)])
pipe2.fit(df_train3, goal_train3)
df_train4 = pipe.transform(df_train3)
df_test4 = pipe.transform(df_test3)
```

In [43]:
```
forest2=RandomForestRegressor(random_state=42)
forest2.fit(df_train4, goal_train3)
forest2_predict = forest2.predict(df_test4)
forest2_mse = np.power(goal_test3 - forest2_predict, 2).mean()
forest2_mse
```

Out[43]:
```
6346.378575722541
```

In [44]:
```
forest2_rmse= forest2_mse **.5
forest2_rmse
```

Out[44]:
```
79.66416117503869
```

In [45]:
```
forest_scores2 = cross_val_score(forest2, df_test4, goal_test3, cv=10)
forest_scores2
```

Out[45]:
```
array([0.78817466, 0.77596259, 0.79245394, 0.83675126, 0.83025825,
       0.84631427, 0.60307723, 0.6617484 , 0.814059  , 0.80734403])
```

In [46]:
```
forest_scores2.mean()
```

Out[46]:
```
0.7756143634832479
```

With an RMSE of 79.66 - around four digits off of the RMSE with imputation - and a cross validation accuracy score of 77.56% - around 2.5% below the accuracy score with imputation - it depends on what metric you focus on to determine which method is better. Dropping the nulls proved to make the model slightly more predictive, yet slightly less accurate. Due to the change in RMSE being larger, I'm going to rely on it for determining the better model. After all, The difference in accuracy scores might not be statistically significant. Therefore I'll forgo imputations in future models.

Predicting Alumni Salary

Due to a lack of subjectivity, alumni salary is a potentially better variable for determining the greatness of a college while also being easier to predict. These algorithms will be designed with the nulls removed instead of estimated.

In [47]:
```
df_corr['Alumni Salary'].sort_values(ascending=False)
```

Out[47]:
```
Alumni Salary                1.000000
SAT Lower                    0.692809
SAT Average                  0.688489
SAT Difference               0.688489
ACT Lower                    0.684012
ACT Difference               0.676508
ACT Average                  0.676508
SAT Upper                    0.665051
ACT Upper                    0.649847
Total Annual Cost            0.398787
Average Grant Aid            0.377548
Post-UG Population           0.320138
Post-UG Percentage           0.297272
Net Price                    0.191580
Student Population           0.107621
Undergraduate Population     0.032952
Public                      -0.045116
Undergraduate Percentage    -0.297272
Acceptance Rate             -0.556903
Rank                        -0.721772
Name: Alumni Salary, dtype: float64
```

As we can see, the variables most correlated to Almunmni Salary are the same variables most correlated to a college's rank.

In [48]:
```
df3=df.dropna()
df_goal4=df3['Net Price'].copy()
df4=df3.drop('Net Price', axis=1)
df_train5, df_test5, goal_train3, goal_test3 = train_test_split(df4, df_goal4
df_train5.head(3)
```

Out[48]:

	Rank	Undergraduate Population	Student Population	Average Grant Aid	Total Annual Cost	Alumni Salary	Acceptance Rate	SAT Lower	SA Uppe
601	602.0	2814.0	3343.0	6195.0	35144.0	81500.0	86.0	990.0	1200.
458	459.0	1043.0	1231.0	22690.0	44408.0	77900.0	91.0	1060.0	1320.
3	4.0	4680.0	11466.0	43248.0	67430.0	155200.0	7.0	1490.0	1570.

In [49]:
```
pipe2.fit(df_train5, goal_train3)
df_train6 = pipe2.transform(df_train5)
df_test6 = pipe2.transform(df_test5)
```

First Model: Random Forest Regressor

In [50]:
```
forest3=RandomForestRegressor(random_state=42)
forest3.fit(df_train6, goal_train3)
forest3_predict = forest3.predict(df_test6)
forest3_mse = np.power(goal_test3 - forest3_predict, 2).mean()
forest3_mse
```

Out[50]: 18774601.68435087

In [51]:
```
forest3_rmse= forest3_mse ** .5
forest3_rmse
```

Out[51]: 4332.966845517153

In [52]:
```
forest_scores3 = cross_val_score(forest3, df_test6, goal_test3, cv=10)
forest_scores3
```

Out[52]:
```
array([0.6849588 , 0.49297163, 0.65751083, 0.69383073, 0.33530305,
       0.72323763, 0.51358294, 0.73420128, 0.65510616, 0.5868688 ])
```

In [53]:
```
forest_scores3.mean()
```

Out[53]: 0.607757186336001

With an RMSE of 4332.96 and an accuracy score of 60.78%, the model's predictions could be better. The RMSE is actually very good as 4332.96 is less than half of a standard deviation for Alumni Salary. Also the range for Alumni Salary is around 80,000, which is several times larger than the RMSE. That being said, the accuracy score from cross validation is only 60.78%, not much better than a coin toss.

Based on it - as well as not havin an Alumni Salary RMSE to compare it to - I believe there is a better model to use to predict alumni salary. As Random Forest Regressors generally prefer more complex data, I'll move on to simpler models.

Second Model: Linear Regression

As before, I'll be using two different methods to build my regression model. This is due to the fact that some information is easier to acquire through the different methods.

In [54]:

```
reg.fit(df_train6, goal_train3)
reg2_predict = reg.predict(df_test6)
reg_mse2 = np.power(goal_test3 - reg2_predict, 2).mean()
reg_mse2
```

Out[54]:

```
16173398.50470559
```

In [55]:

```
reg_rmse2 = reg_mse2 ** .5
reg_rmse2
```

Out[55]:

```
4021.61640447042
```

In [56]:

```
reg2_scores = cross_val_score(reg, df_test6, goal_test3, cv=10)
reg2_scores
```

Out[56]:

```
array([0.65835473, 0.50046384, 0.73517647, 0.8845713 , 0.81058023,
       0.72947146, 0.67998092, 0.79991371, 0.69276538, 0.5845141 ])
```

In [57]:

```
reg2_scores.mean()
```

Out[57]:

```
0.7075792138743544
```

As I expected, both the RMSE and the accuracy score have been improved by using a linear regression model. The RMSE have dropped by 300 points, or a 7% improvement. While the accuracy score has increased by 10% to 70%, much more respectable.

In [58]:
```
x=sm.add_constant(df_train6)
model = sm.OLS(goal_train3, x)
results = model.fit()
results.summary()
```

Out[58]:

OLS Regression Results

Dep. Variable:	Net Price	**R-squared:**	0.776
Model:	OLS	**Adj. R-squared:**	0.768
Method:	Least Squares	**F-statistic:**	90.02
Date:	Mon, 13 Sep 2021	**Prob (F-statistic):**	4.10e-101
Time:	20:50:11	**Log-Likelihood:**	-3368.1
No. Observations:	351	**AIC:**	6764.
Df Residuals:	337	**BIC:**	6818.
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	2.249e+04	193.808	116.040	0.000	2.21e+04	2.29e+04
x1	402.8923	434.024	0.928	0.354	-450.845	1256.630
x2	-383.5865	240.375	-1.596	0.111	-856.410	89.237
x3	-330.4238	142.520	-2.318	0.021	-610.765	-50.082
x4	-7876.0109	537.182	-14.662	0.000	-8932.662	-6819.360
x5	7425.8739	477.425	15.554	0.000	6486.765	8364.983
x6	98.3172	315.230	0.312	0.755	-521.749	718.383
x7	436.7279	328.859	1.328	0.185	-210.147	1083.603
x8	-186.6839	746.319	-0.250	0.803	-1654.714	1281.346
x9	809.7023	721.777	1.122	0.263	-610.054	2229.459
x10	1786.3811	758.727	2.354	0.019	293.945	3278.818
x11	-1924.9865	762.068	-2.526	0.012	-3423.996	-425.977
x12	286.5902	175.280	1.635	0.103	-58.190	631.371
x13	122.8545	190.536	0.645	0.520	-251.935	497.644
x14	-5897.5446	394.822	-14.937	0.000	-6674.170	-5120.919
x15	-258.0653	154.160	-1.674	0.095	-561.302	45.172
x16	122.8545	190.536	0.645	0.520	-251.935	497.644
x17	286.5902	175.280	1.635	0.103	-58.190	631.371
x18	-28.2732	382.310	-0.074	0.941	-780.288	723.741
x19	258.0653	154.160	1.674	0.095	-45.172	561.302

Omnibus:	32.740	**Durbin-Watson:**	1.893

Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	63.552
Skew:	0.531	**Prob(JB):**	1.58e-14
Kurtosis:	4.794	**Cond. No.**	2.60e+16

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 5.74e-30. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

There is some more information to be gleamed. Based on an an alternative hypothesis with a 95% confidence threshold, most of the variables in this regression would be found statistically insiginficant. It also has an R-squared value of 77.6%, which is a respectable R-squared value. Based on the regression, it seems that simpler algorithms offer better predictions when determining Alumni Salary, so it's best to try an even simpler model.

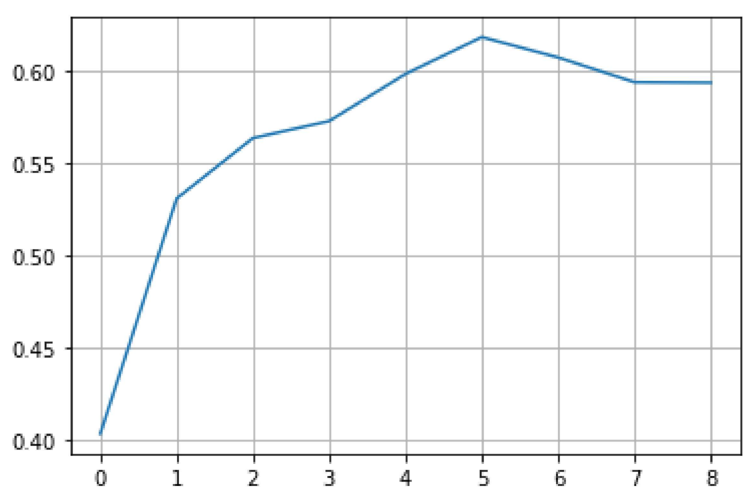
Third Model: K-Nearest Neighbors

In [59]:

```
n_neighbors =list(range(1, 10))
accuracy = []
for neighbor in n_neighbors:
    clf = KNeighborsRegressor(n_neighbors = neighbor)
    clf.fit(df_train6, goal_train3)
    score = clf.score(df_test6, goal_test3)
    accuracy.append(score)
plt.grid(True)
plt.plot(accuracy)
```

Out[59]:

```
[<matplotlib.lines.Line2D at 0x1f0555feee0>]
```



In [60]:

```
knn2 = KNeighborsRegressor(n_neighbors = 5)
knn2.fit(df_train6, goal_train3)
knn2_predict = knn2.predict(df_test6)
knn_mse2 = np.power(goal_test3 - knn2_predict, 2).mean()
```

In [61]:
```
knn_rmse2 = knn_mse2 ** .5
knn_rmse2
```

Out[61]: 5254.1800195136675

In [62]:
```
knn2_scores = cross_val_score(knn2, df_test6, goal_test3, cv=10)
knn2_scores
```

Out[62]:
```
array([0.46883649, 0.46369285, 0.59270023, 0.56427594, 0.33024053,
       0.53479367, 0.55311628, 0.36523227, 0.56416681, 0.49563041])
```

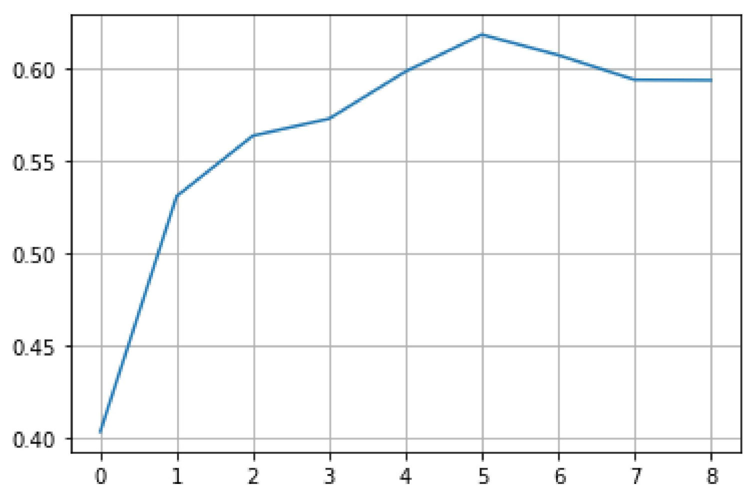
In [63]:
```
knn2_scores.mean()
```

Out[63]: 0.4932685475870634

Interestingly this model performed the worst out of all the models. It had the worst RMSE and its accurac score is around 20% lower than the regression. Therefore the regression model is the model to use when predicting Alumni Salary.

In [64]:
```
n_neighbors =list(range(1, 10))
accuracy = []
for neighbor in n_neighbors:
    clf = KNeighborsRegressor(n_neighbors = neighbor)
    clf.fit(df_train6, goal_train3)
    score = clf.score(df_test6, goal_test3)
    accuracy.append(score)
plt.grid(True)
plt.plot(accuracy)
```

Out[64]: [<matplotlib.lines.Line2D at 0x1f055661ee0>]



As the model is already at its more effective number of neighbors, there is little that can be done to improve on the model. Therefore, the linear regression model is the best predictor of alumni salary.

In [65]:
```
df.to_excel[redacted]ndex = False)
```