Simulations Homework

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
%matplotlib inline
```

Reset Generator Function

If you didn't do so in class, write a function to reseed the numpy random number generator. It should default to setting the seed to 42, but be able to set it to whatever you want.

In [2]:
```
def reset_rng(seed=42):
    rng = np.random.default_rng(seed)

    return rng
```

Reset the generator using your function.

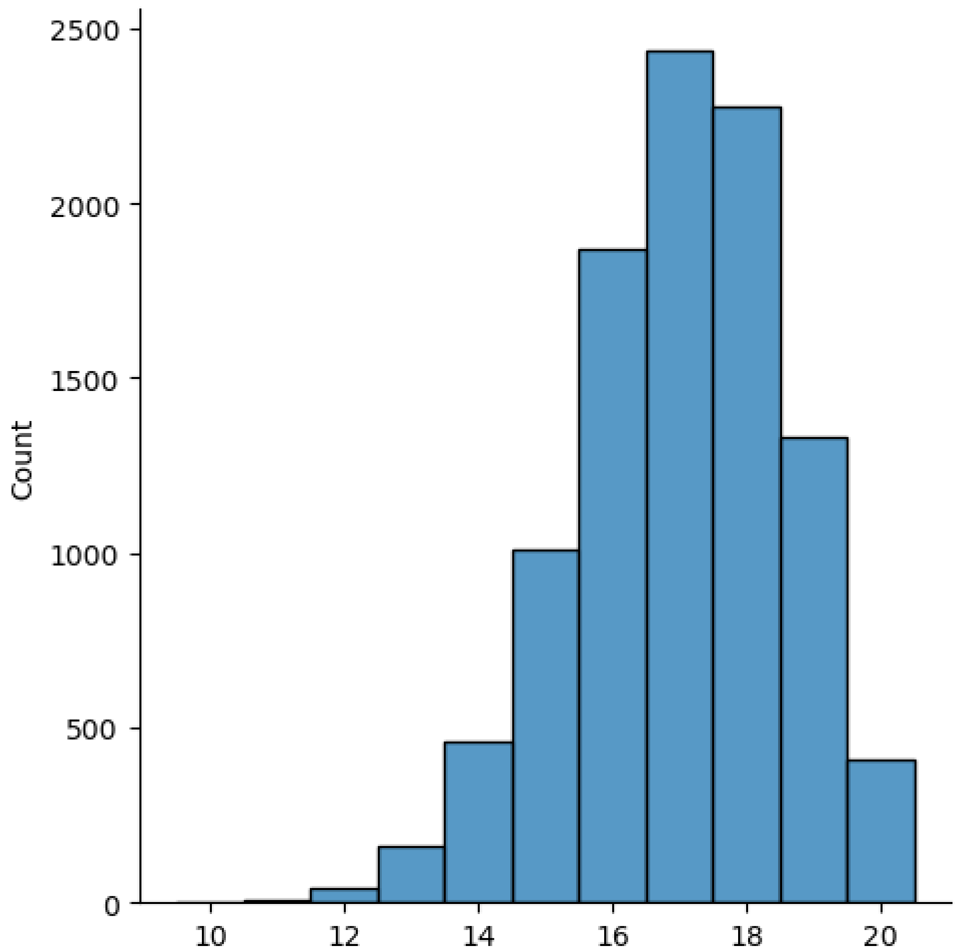
In [26]:
```
rng = reset_rng()
```

"Accept Cookies" Simulation

Assuming the base rate for hitting the "Accept Cookies" button when landing on a website is 85%, do a set of 10,000 simulations of 20 people visiting a given website and accepting cookies.

In [31]:
```
n_sample = 20
prob = .85
n_sim = 10000
cookies_sim = rng.binomial(n_sample, prob, n_sim)
sns.displot(cookies_sim, discrete=True)
```

Out[31]: <seaborn.axisgrid.FacetGrid at 0x7f77d81374f0>



Based on your simulation, what is the probability of getting exactly 15 accepts?

In [32]:
```
p15 = sum(cookies_sim==15)/len(cookies_sim)
p15
```

Out[32]: 0.101

What is the probability of getting *at least* 15 accepts?

In [33]:
```
pAtLeast15 = sum(cookies_sim>=15)/len(cookies_sim)
pAtLeast15
```

Out[33]: 0.9326

What is the probability of getting fewer than 15 accepts?

In [34]:
```
pLess15 = sum(cookies_sim<15)/len(cookies_sim)
pLess15
```

Out[34]: 0.0674

Confirm that the last two probabilities computed sum to 1.0.

In [35]:
```
pAtLeast15 + pLess15
```

Out[35]: 1.0

What Is and Isn't Binomial?

Check the binomial approximation for the election simulations from the in-class notebook for the cases in which we did and didn't account for the poll-to-poll variability arising from a single poll.

What is the expected standard deviation for our distribution of election outcomes based on the normal approximation?

In [36]:
```
# set the constants
n_sample = 100000 # number of voters in the election
prob =.51 # probability that they vote for A
n_sim = 100000 # number of election simulations

# determine the sd
sd_est = np.sqrt(n_sample * prob * (1 - prob))
sd_est
```

Out[36]: 158.082257068907

What was the empirical standard deviation of the distribution of election outcomes when we only used a single probability? ("*single poll, many elections*")

(You can just copy and paste the code from the in-class notebook to regenerate the simulated election outcomes.)

In [37]:
```
rng = reset_rng()
election_outcomes = rng.binomial(n=100000, p=.51, size=20000)
```

In [38]:
```
np.std(election_outcomes)
```

Out[38]: 158.93412097331398

What was the empirical standard deviation of the distribution of election outcomes when we accounted for random variation in poll outcomes in our simulation? ("*simulate poll -> simulate*

In [39]:
```
rng = reset_rng()
# constants
prob = .51  # best guess of "true" probability
sample = 2000  # poll sample size
sims = 100000  # number of simulations to run
# conduct polls
poll_results = rng.binomial(n=sample, p=prob, size=sims) # get the polling
poll_probs = poll_results/sample  # convert to probabilities
# simulate the elections
sample=100000 # medium city - expect around 100k voter turnout
election_outcomes = rng.binomial(n=sample, p=poll_probs, size=sims)
```

In [40]:
```
np.std(election_outcomes)
```

Out[40]:
```
1126.0395066316592
```

When we simulate the poll to include variability in our election results, the election outcomes are no longer part of a binomial distribution

---

Effect of Poll Sample Size

As you have probably realized, these distributions of outcomes from many experiments we've been generating are, by definition, ***sampling distributions***! One firm law about sampling distributions is that their width depends strongly on sample size. As such, we would expect our simulated election outcomes to be affected by the size of the poll on which they are based.

In the cell below, run the *simulate poll* -> *simulate elections* code for poll sample sizes of 50, 100, 500, 1000, 2000 and 5000. For each sample size, record the obtained standard deviation of the distribution of outcomes. (pro tip: make a new code cell below and put them in a Python list)

In [43]:
```
 rng = reset_rng() # reset generator
```

In [44]:
```
sample_sizes = [50, 100, 500, 1000, 2000, 5000]
```

In [45]:
```
# simulate
# constants
prob = .51  # best guess of "true" probability
sample = 2000  # poll sample size
sims = 100000  # number of simulations to run
d = {}
for i in range(len(sample_sizes)):
    # conduct polls
    print(sample_sizes[i])
    poll_results = rng.binomial(n=sample_sizes[i], p=prob, size=sims) # get
    poll_probs = poll_results/sample_sizes[i]  # convert to probabilities
    # simulate the elections
    sample=100000 # medium city - expect around 100k voter turnout
    d["poll_size_of_{0}".format(sample_sizes[i])] = rng.binomial(n=sample,
election_outcomes = pd.DataFrame(d)
election_outcomes
```

```
50
100
500
1000
2000
5000
```

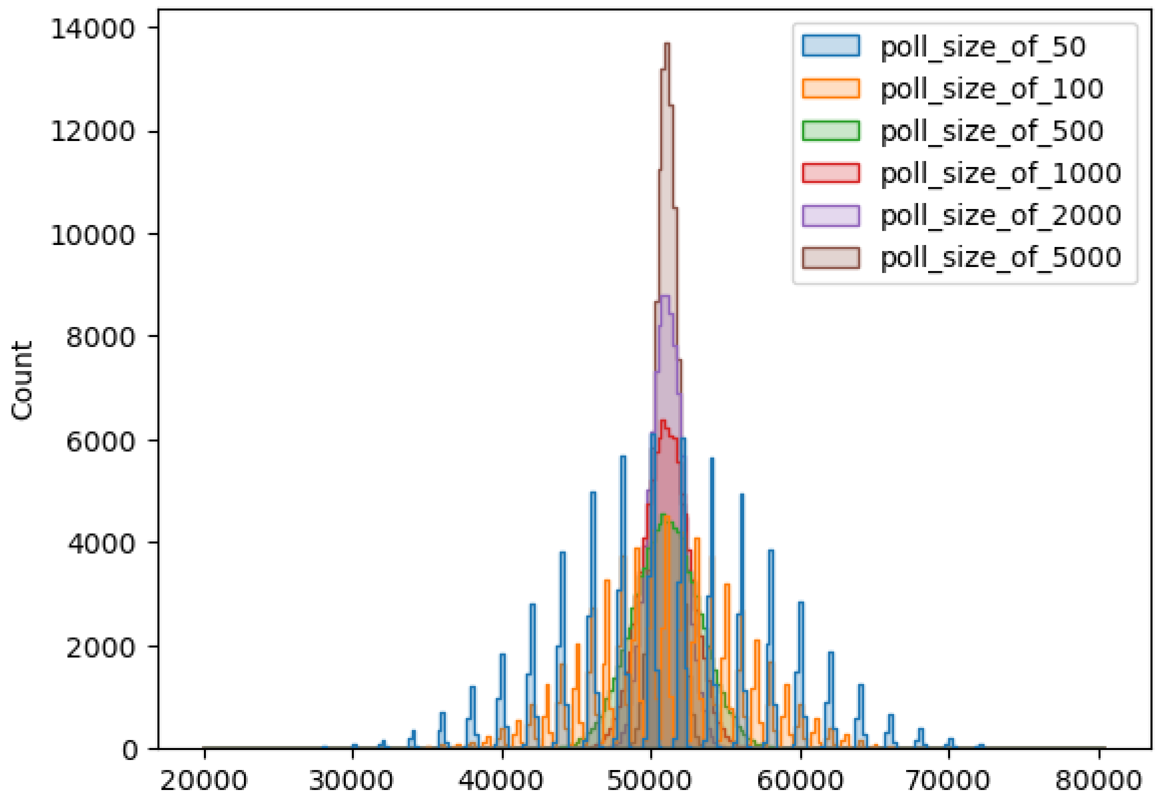
Out[45]:

	poll_size_of_50	poll_size_of_100	poll_size_of_500	poll_size_of_1000	poll_size_of_2000	poll_siz
0	46158	60275	49729	48826	49524	
1	51890	49205	51074	50805	51059	
2	43927	51152	54739	50266	50566	
3	47880	46229	52591	50724	51143	
4	59838	48778	52816	49808	49027	
...	...	...	...	...	...	
99995	55902	45014	46888	54134	48694	
99996	49771	45121	49123	46567	50227	
99997	50113	43023	55737	53317	51195	
99998	59926	51043	50233	51219	52504	
99999	39806	53137	52043	51824	51532	

100000 rows × 6 columns

In [52]:
```
sns.histplot(election_outcomes, binwidth=250, element='step')
```

Out[52]: <AxesSubplot:ylabel='Count'>

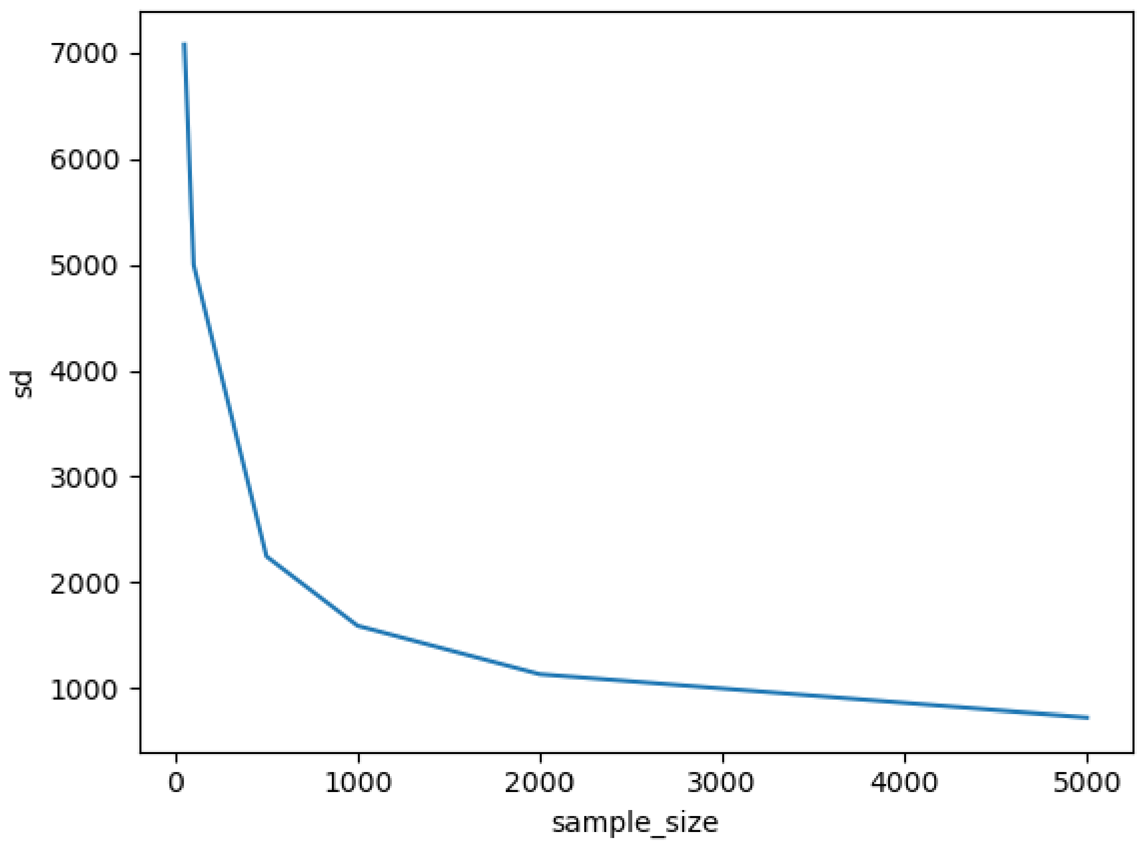


Make a plot of standard deviation of outcomes (y-axis) vs. poll sample size (x-axis).

In [53]:
```
# make df of sd and n
election_outcomes_sd_n = pd.DataFrame(election_outcomes.agg(np.std))
election_outcomes_sd_n['sample_size'] = sample_sizes
election_outcomes_sd_n = election_outcomes_sd_n.rename(columns={0:'sd'})
display(election_outcomes_sd_n)
# plot
sns.lineplot(data=election_outcomes_sd_n, x='sample_size', y='sd')
```

	sd	sample_size
poll_size_of_50	7077.253081	50
poll_size_of_100	4997.644691	100
poll_size_of_500	2244.258856	500
poll_size_of_1000	1588.170982	1000
poll_size_of_2000	1129.921183	2000
poll_size_of_5000	723.675043	5000

Out[53]: <AxesSubplot:xlabel='sample_size', ylabel='sd'>



Based on this plot, why do you think almost all polls sample around 2000 people?

Most people probably sample around 2000 people because you get diminishing returns as you sample more people. Sampling more people beyond 2000 doesn't decrease the standard deviation in proportion to the sample size that much

Re-Write the Multi-Poll Code

The code for combining three polls using a weighted average works, but it is awkward. Changing it to handle a different number of polls would involve lots of copying and pasting and mistake-prone editing.

Make the code "Pythonic" so that all you have to do is provide a list (or tuple) of poll results and another for poll weights, and your code will do the rest.

Your code can be just code in a code cell. But if you're feeling spicy, you could make it a function!

In [55]:
```
# first, without a function
# reset the seed
rng = reset_rng()
# set the constants
poll_ests = [0.53, 0.51, 0.515]
poll_weights = [2, 4, 3]
sum_of_w = np.sum(poll_weights)
samp_sz = 2000                      # poll sample size
n_sims = 20000                      # number of simulations to run
# conduct the polls, accounting for their variance
poll_results = {}
poll_probs = {}
for i in range(len(poll_ests)):
    poll_results[i] = rng.binomial(samp_sz, poll_ests[i], n_sims)
    poll_probs[i] = poll_results[i]/samp_sz
# simulate the elections for each poll
elec_results_per_poll = {}
n_voters = 100000
for i in range(len(poll_ests)):
    elec_results_per_poll[i] = rng.binomial(n_voters, poll_probs[i], n_sims
# weight the election results per poll
weighted_elec_results_per_poll = {}
for i in range(len(poll_ests)):
    weighted_elec_results_per_poll[i] = elec_results_per_poll[i]*poll_weigh
weighted_elec_results_per_poll = pd.DataFrame(weighted_elec_results_per_pol
elec_results = weighted_elec_results_per_poll.sum(axis=1)/sum_of_w # sum th
elec_results
```

Out[55]:
```
0        52007.333333
1        52980.222222
2        51483.000000
3        51200.555556
4        51290.333333
             ...
19995    52034.111111
19996    52491.111111
19997    51883.333333
19998    52402.333333
19999    51065.888889
Length: 20000, dtype: float64
```

In [56]:
```
# now with a function
# every argument has a default
# went ahead and enabled customizable samp_sz
def multi_poll_sim(poll_ests = [0.53, 0.51, 0.515], poll_weights = [2, 4, 3
    # set the constants
    sum_of_w = np.sum(poll_weights)
    # conduct the polls, accounting for their variance
    poll_results = {}
    poll_probs = {}
    for i in range(len(poll_ests)):
        poll_results[i] = rng.binomial(samp_sz[i], poll_ests[i], n_sims)
        poll_probs[i] = poll_results[i]/samp_sz[i]
    # simulate the elections for each poll
    elec_results_per_poll = {}
    for i in range(len(poll_ests)):
        elec_results_per_poll[i] = rng.binomial(n_voters, poll_probs[i], n_
    # weight the election results per poll
        weighted_elec_results_per_poll = {}
    for i in range(len(poll_ests)):
        weighted_elec_results_per_poll[i] = elec_results_per_poll[i]*poll_w
    weighted_elec_results_per_poll = pd.DataFrame(weighted_elec_results_per
    elec_results = weighted_elec_results_per_poll.sum(axis=1)/sum_of_w # su

    return elec_results
```

In [57]:
```
# testing my function
rng = reset_rng()
elec_results = multi_poll_sim()
elec_results
```

Out[57]:
```
0        52007.333333
1        52980.222222
2        51483.000000
3        51200.555556
4        51290.333333
             ...
19995    52034.111111
19996    52491.111111
19997    51883.333333
19998    52402.333333
19999    51065.888889
Length: 20000, dtype: float64
```

In [58]:
```
# testing my function
rng = reset_rng()
elec_results = multi_poll_sim(poll_weights=[1000, 2000, 3000], samp_sz = [1
elec_results
```

Out[58]:
```
0        52013.666667
1        51100.833333
2        52545.833333
3        52654.333333
4        51409.500000
             ...
19995    52146.833333
19996    51782.500000
19997    51108.500000
19998    50822.000000
19999    51566.000000
Length: 20000, dtype: float64
```

Weight polls by sample size

Use your new code to compute predicted election outcomes based on 5 polls weighted by the sample sizes of the polls (or their square root, if you prefer – wink wink, nudge nudge). The polls are as follows:

```
poll_ests = [.51, .55, .53, .49, 0.50]
```

```
poll_samp_szs = [2000, 1000, 1500, 1200, 1142]
```

In [59]:
```
rng = reset_rng() # rset the seed
new_poll_ests = [.51, .55, .53, .49, .5]
new_samp_szs = [2000, 1000, 1500, 1200, 1142]
new_weights = np.sqrt(new_samp_szs)
elec_results = multi_poll_sim(poll_ests=new_poll_ests, poll_weights=new_wei
elec_results
```

Out[59]:
```
0        51822.789250
1        52087.959331
2        51534.541859
3        52107.966563
4        51679.670774
             ...
19995    51905.732536
19996    51562.650199
19997    50834.648022
19998    51383.395449
19999    50873.512505
Length: 20000, dtype: float64
```

Make a plot of the distribution of simulated outcomes, with the area representing the underdog winning highlighted.

In [60]:
```
# create a new column for elec resutls to map onto hue
wins = []
for i in range(len(elec_results)):
    if elec_results[i] >= 50000:
        wins.append("Favorite")
    else:
        wins.append("Underdog")
elec_results = pd.DataFrame(elec_results)
elec_results['wins'] = wins
elec_results = elec_results.rename(columns={0:'votes_for_favorite'})
elec_results
```

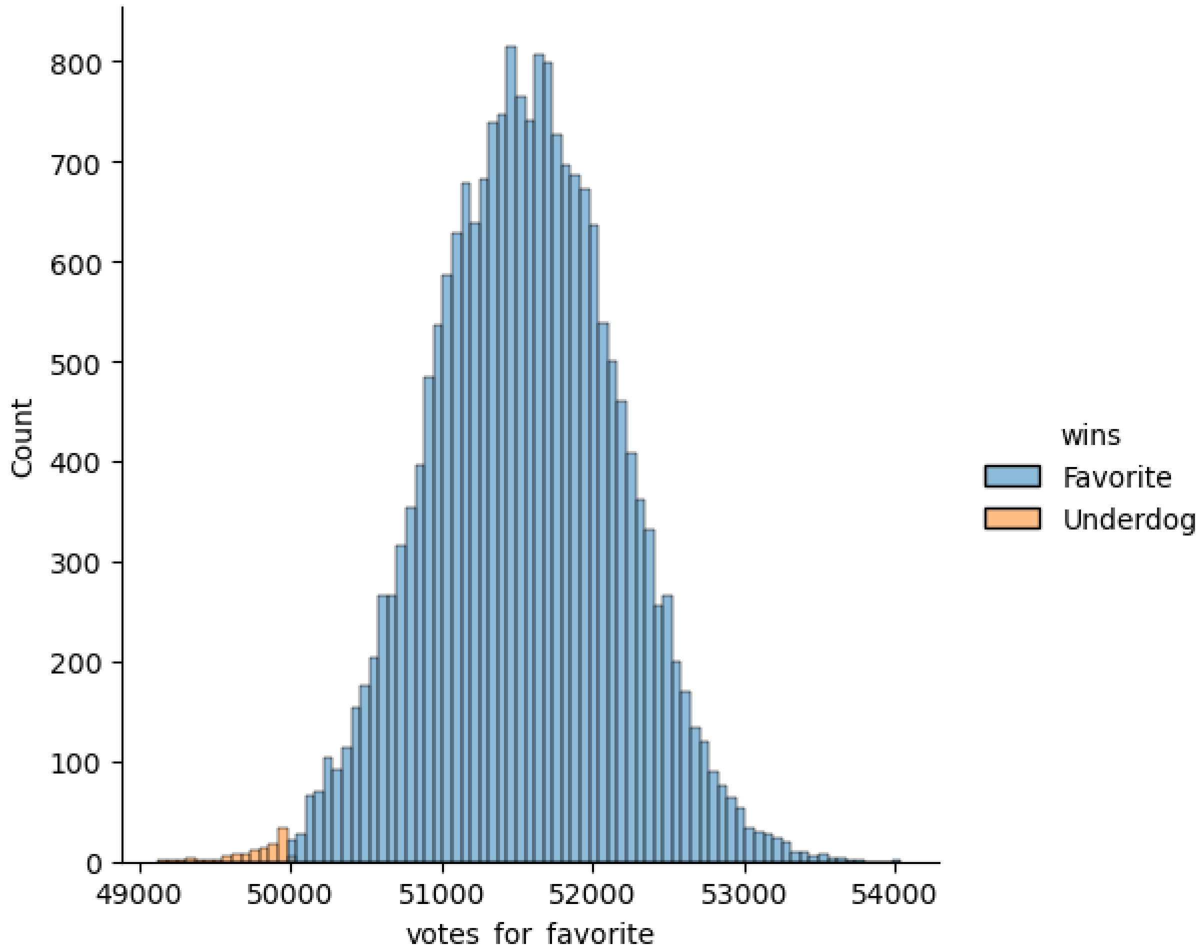
Out[60]:

	votes_for_favorite	wins
0	51822.789250	Favorite
1	52087.959331	Favorite
2	51534.541859	Favorite
3	52107.966563	Favorite
4	51679.670774	Favorite
...	...	...
19995	51905.732536	Favorite
19996	51562.650199	Favorite
19997	50834.648022	Favorite
19998	51383.395449	Favorite
19999	50873.512505	Favorite

20000 rows × 2 columns

In [61]:
```
sns.displot(elec_results, x='votes_for_favorite', hue='wins')
```

Out[61]: <seaborn.axisgrid.FacetGrid at 0x7f77d8a282b0>



Bonus (totally optional): Write your own function, `my_binom()` that does the same thing as `rng.binomial()`. The function should use `rng.random()` internally. To the user, it should behave just like `rng.binomial()`!

In [ ]: