Overview of the rest of the term

- final project submission deeadline: December 3, 11:59pm
- final project presentations: December 4, 5, 6, 4pm to 6:30pm in 275 (one floor below DSI)
- thursday's lecture is review
  - bring questions or ask me on piazza
- final exam: December 10
  - closed book written exam, lasts an hour
- grades by December 17-18
- final grades submitted by December 20

Deployment and continuous monitoring

By the end of this lecture, you will be able to

- Describe A/B testing and when it's not the right approach to test
- Describe common challenges with deployment
- Develop strategies to monitor a deployed ML model

- you put together the ML pipeline (splitting, preprocessing, parameter tuning)
- tried a couple of supervised ML algorithms
- you have a test score with uncertainty
- feature importance metrics
- you understand and trust your model ## **...** now what?

It is time to deploy the model!

- up to now you played in a sandbox
  - you worked with historical data
  - no actual decisions were made based on the work you did so far
- once your model is deployed, it will replace whatever decision making process was in place until now
  - this is done carefully and gradually

Typical scenario

- you get more recent data and you need to apply your model to it (pre-deployment)
- A/B testing (your model is partially deployed)
  - evidence-based comparison of the ML approach and the previous decision making process
- if your model is better than the previous decision making process, your model will replace it (full deployment)

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- **Describe A/B testing and when it's not the right approach to test**
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A/B testing - example

My project with Advancement

- goal: predict how much alumni will donate in the upcoming fiscal year
  - the predictions are used as target ask amounts in phone/mail/email communication
- previous decision making process:
  - a group of experts meet regularly for a couple of weeks to discuss the what a good target ask amount is
  - very labor-intensive and also somewhat subjective
- a regression model was developed by my colleague and myself with R2 scores in the range of 0.7-0.8
- it was time to test it

A/B testing - example

- Advancement created two groups:
  - group A (control) - the previous decision making process was used to generate target ask amounts
  - group B (treatment) - the regression model's prediction were used
- alumni were randomly assigned to the two groups
  - we checked that key demographic groups (race/gender/ethnicity) were more or less evenly distributed in the two groups
- the only difference between the two groups were the decision making process used, everything else was the same.
- we waited a year :D

A/B testing - example

- we compared the donations given by the two groups using statistical tests
  - we used a two sided t test to compare the donation distributions in groups A and B
- unfortunately we found that my model does not increase the amount the alumni donate
- the model was still adopted by Advancement because it saves a ton of work for them
  - several people's work time freed up so they can do better, more important things now
- this year, my model completely replaced Advancement's previous decision making process

A/B testing - general concept

- create two groups usually semi-randomly
  - if you have segments (groups of interest), make sure that the segments are more or less evenly represented in both groups
- the two groups are similar in all but one aspect
  - group A (control): the previous decision making process is applied on them
  - group B (treatment): your new ML model is applied on them
- wait for the results to come in
- use a statistical test to compare the target variable of the two groups (see here (https://en.wikipedia.org/wiki/A/B_testing#Common_test_statistics))

A/B testing - estimate sample size

- How many people should be in the two groups?
  - Do we have segments?
  - What difference in performance would you expect between the previous and the new decision making process?
  - What is the distribution/type of the target variable? (determines the test you should use)
  - What significance level (p value) would you like to achieve?

A/B testing - estimate sample size

An example:

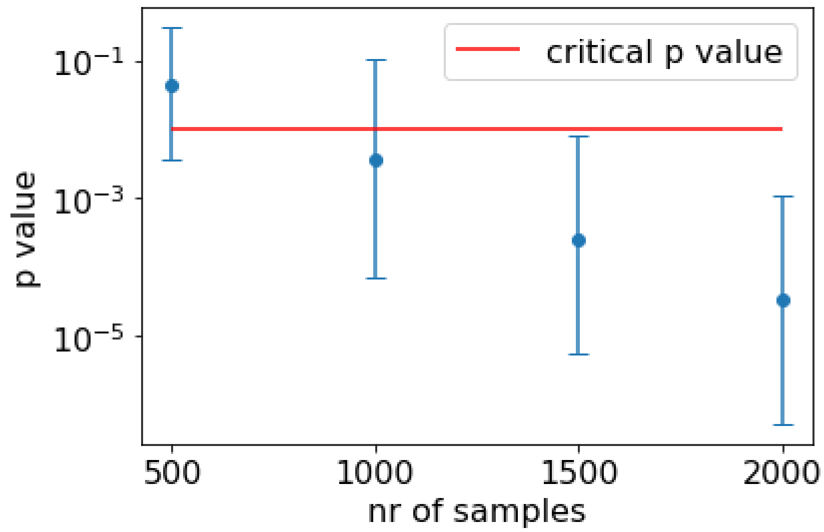
- we have segments
- we have a classification model and the difference in accuracy is 5% between the previous and new processes
  - previous process has an 80% accuracy
  - new process has an 85% expected accuracy based on the mean test score
- target variable is binary, we want to compare odds ratios (Fischer's exact test)
- we are interested in a 0.01 or lower p value
- **let's simulate this to estimate the sample size**

In [12]:
```
import numpy as np
import scipy.stats as stats
np.random.seed(0)
n_samples = [500,1000,1500,2000] # sample size in a segment
A_acc = 0.8 # accuracy in the control group
B_acc = 0.85 # expected accuracy in the treatment group

# let's loop through n, simulate data, apply t test to simulated data
median_p = np.zeros(len(n_samples))
upper_p = np.zeros(len(n_samples))
lower_p = np.zeros(len(n_samples))
for n in range(len(n_samples)):
    p_vals = []
    for i in range(100):
        A_results = np.random.choice([0, 1], size=(n_samples[n]), p=[1-A
_acc, A_acc])
        B_results = np.random.choice([0, 1], size=(n_samples[n]), p=[1-B
_acc, B_acc])
        oddsratio, pvalue = stats.fisher_exact([[sum(A_results==0), sum(
A_results==1)], [sum(B_results==0), sum(B_results==1)]])
        p_vals.append(pvalue)

    median_p[n] = np.median(p_vals)
    upper_p[n] = np.percentile(p_vals,84) # you can also do np.max(p_val
s)
    lower_p[n] = np.percentile(p_vals,16) # you can also do np.min(p_val
s)
```

In [13]:
```
import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams.update({'font.size': 16})
plt.errorbar(n_samples,median_p,yerr=np.array([median_p-lower_p,upper_p-median_p]),capsize=5,fmt='o')
plt.hlines(0.01,n_samples[0],n_samples[-1],color='r',label='critical p value')
plt.xlabel('nr of samples')
plt.ylabel('p value')
plt.semilogy()
plt.legend()
plt.show()
```



A/B testing - when it is not the right approach

- testing is not ethical
  - [facebook scandal (https://techcrunch.com/2014/06/29/ethics-in-a-data-driven-world/)](https://techcrunch.com/2014/06/29/ethics-in-a-data-driven-world/)
  - you need approval from Ethics Board or IRB
- testing is approved but you want to minimize variations in user experience
  - you shouldn't ask different users to pay different amounts for the same service
  - they will start to complain :)
  - multi-armed bandit is a good alternative to minimize costs like this (read about it [here (https://en.wikipedia.org/wiki/Multi-armed_bandit)](https://en.wikipedia.org/wiki/Multi-armed_bandit) and [here (https://towardsdatascience.com/when-and-when-not-to-a-b-test-c901f3ad96d9)](https://towardsdatascience.com/when-and-when-not-to-a-b-test-c901f3ad96d9))

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- Describe A/B testing and when it's not the right approach to test
- **Describe common challenges with deployment**
- Develop strategies to monitor a deployed ML model

Once the model is tested and deployed, you are not done

- incoming data properties can change
  - feature distributions could slowly move away from what you had in training
  - category ratios could change
  - new classes could appear
  - outliers in regression could become the new norm

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- Describe common challenges with deployment
- **Develop strategies to monitor a deployed ML model**

What to do?

- incoming data needs to be monitored
- keep an eye on feature statistics and the target variable properties
- if you see the data changing, retrain your model

By now you know

- Describe A/B testing and when it's not the right approach to test
- Describe common challenges with deployment
- Develop strategies to monitor a deployed ML model