Test Collection Experimentation

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Outline

Parameter Tuning

Cross-validation

Significance testing

Parameter Tuning

motivation

- Search algorithms have lots of moving parts
- We can think of these parameters as “knobs” that need to be tweaked or tuned
- Objective:
  - Find the parameter values that maximize performance (e.g., average P@10)
  - Estimate how well the system will perform using the optimal parameter values
- Can you think of some example parameters?

Parameter Tuning

- Query-likelihood model with linear interpolation

$$score(Q, D) = \prod_{q \in Q} (\lambda P(q|\theta_D) + (1 - \lambda) P(q|\theta_C))$$

- Parameter λ avoids zero probabilities when a document is missing a query-term
- How should we determine the best value of λ and how should we estimate performance with this value?

Parameter Tuning

- How should we determine the value of λ ?
- Option -2: roll the dice, close your eyes, and hope for the best
- Option -1: take a conservative guess (e.g., $\lambda = 0.5$)?
- Option 0: take an "intuitive" guess (e.g., $\lambda = 0.7$)?
- Option 1: try out a range of values (e.g., $\lambda = 0.0, 0.1, 0.2, ..., 1.0$) and set it to the value that maximizes performance based on a sensible metric?

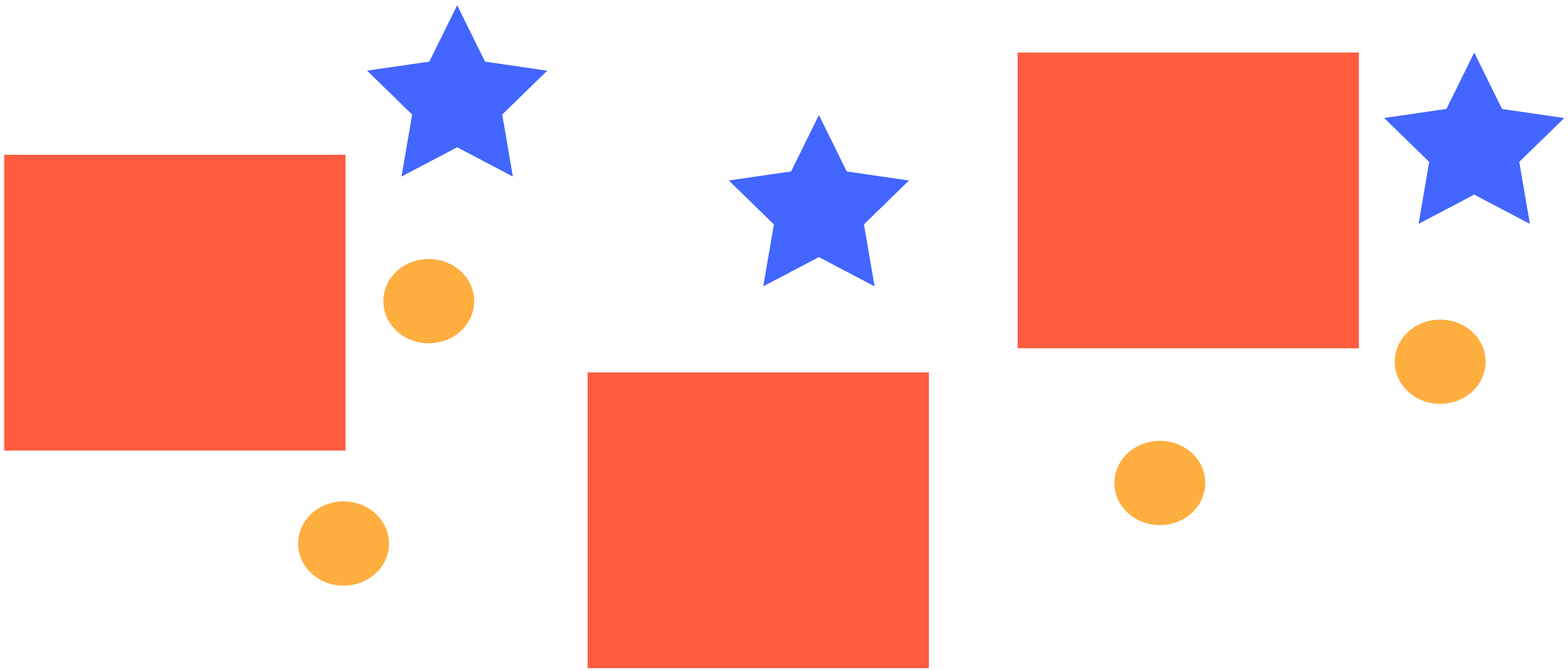
Parameter Tuning

λ =	Average P@10 =
0.0	0.25
0.1	0.27
0.2	0.29
0.3	0.35
0.4	0.45
0.5	0.50
0.6	**0.55**
0.7	0.47
0.8	0.35
0.9	0.20
1.0	0.00

How well will the QL model do after parameter tuning?

Parameter Tuning
toy example

- Objective: distinguish between stars, squares, and circles



- Parameters: the relative importance between (1) size, (2) color, and (3) number of sides

Parameter Tuning

- The goal is to estimate the model performance using the optimal parameter values
- What is the performance that we are really interested in?

Parameter Tuning

- The goal is to estimate the model performance using the optimal parameter values
- What is the performance that we are really interested in?
- Performance on <u>previously unseen</u> queries!
- We care about <u>generalization</u> performance!
- Our sample of queries may contain regularities that are not meaningful
- We care about those regularities that generalize to new queries!

Parameter Tuning

λ =		Average P@10 =
0.0		0.25
0.1		0.27
0.2		0.29
0.3		0.35
0.4		0.45
0.5	50 TEST QUERIES	0.50
0.6		**0.55**
0.7		0.47
0.8		0.35
0.9		0.20
1.0		0.00

Why is **0.55** a bad estimate of performance on new queries?

Parameter Tuning

- Option 2:
  1. divide the set of 50 queries into two sets:
     - training set: a set of queries used to find the best parameter values (e.g., 40 queries)
     - test set: a held-out set used to evaluate model performance (e.g., 10 queries)
  2. train: find the parameter value that maximizes average performance on the training set
  3. test: evaluate the model (with the best training-set parameter value) on the test set

Parameter Tuning

DATASET
(50 queries)

Parameter Tuning

- Split the data into two sets.
- Find the parameter value that maximize average performance on the training set.
- Evaluate the system with that parameter value on the test set.

TRAINING SET (40 queries)

$\lambda = 0.6$

TEST SET (10 queries)

P@10 = 0.50

Parameter Tuning

- Split the data into two sets.
- Find the parameter value that maximize average performance on the training set.
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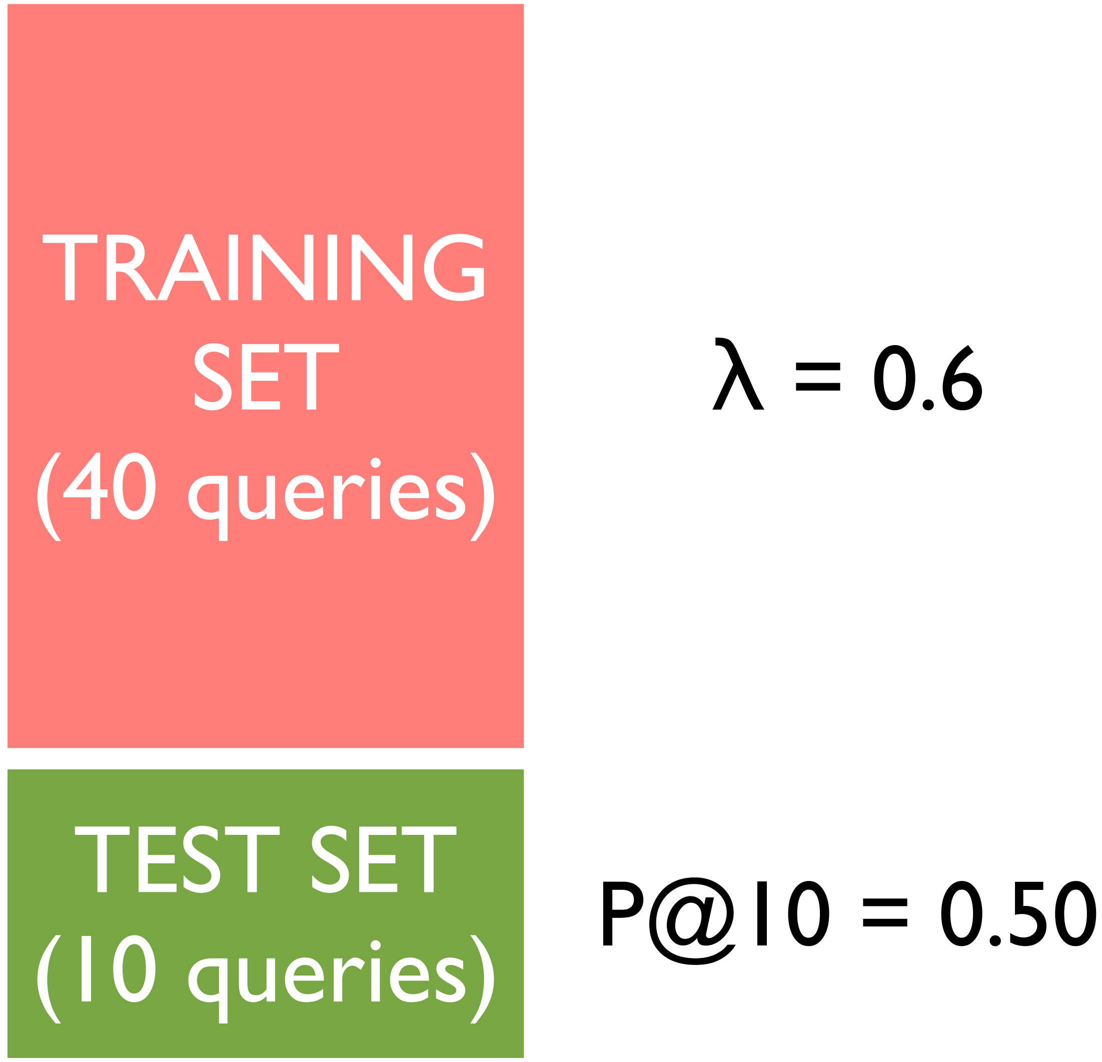


Advantages and Disadvantages?

Single Train/Test Split

- Advantage
  - the data used to find the optimal parameter value is not the same data used to test!
  - we are testing generalization performance.
- Disadvantage
  - we are putting all our eggs in one basket!
  - out of pure coincidence, the training set may have regularities that don't generalize to the test set

Parameter Tuning

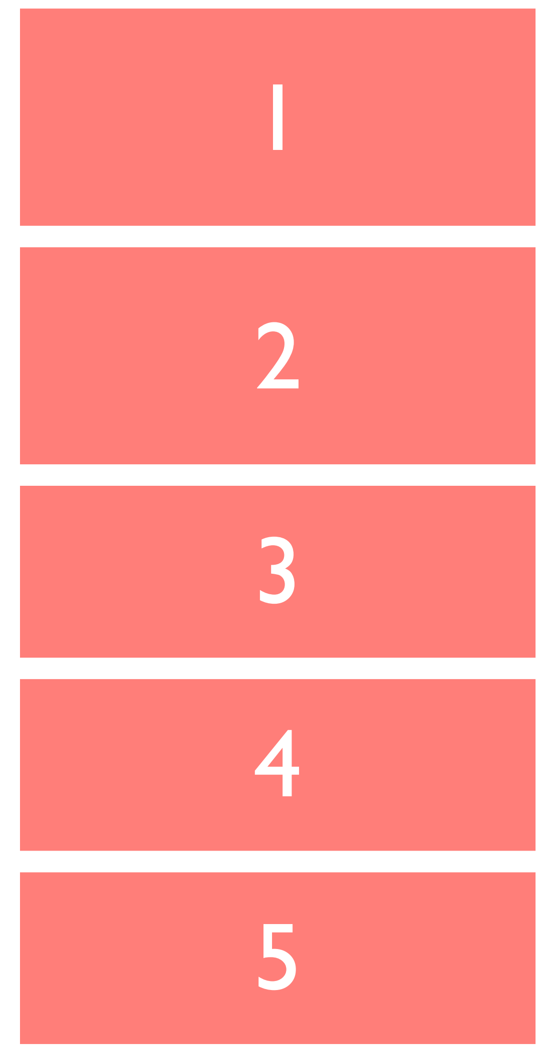
- Option 3: cross-validation
  1. divide the set of 50 queries into N sets of 50/N queries
  2. use the union of N-1 sets to find the best parameter values
  3. measure performance (using the best parameters) on the held-out set
  4. do steps 2-3 N times
  5. average performance across the N held-out sets
- This is called N-fold cross-validation (usually, N=10)

Cross-Validation

DATASET
(50 queries)

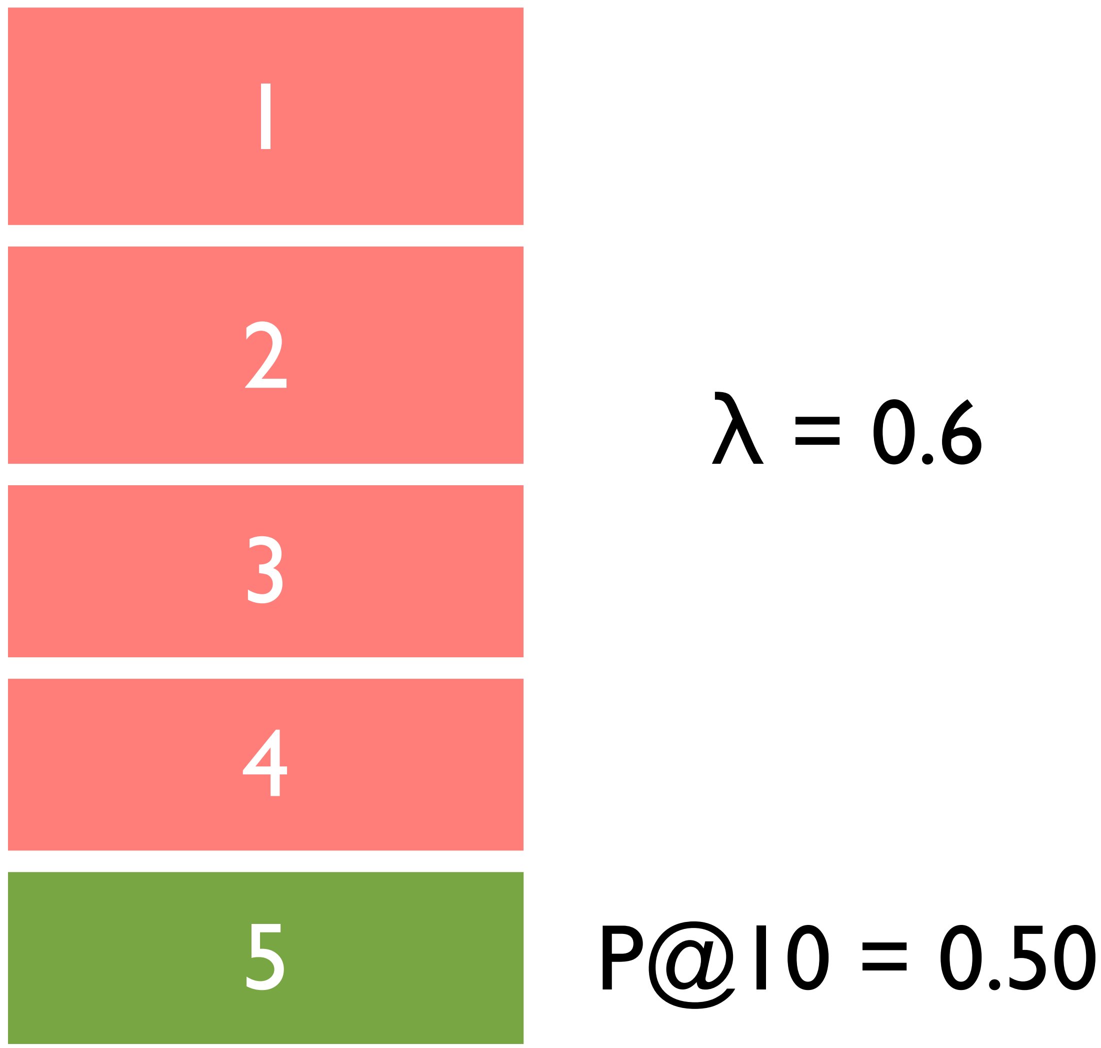
Cross-Validation

- Split the data into N = 5 folds of 10 queries each



Cross-Validation

- For each fold, find the parameter value that maximizes average performance on the union of N - 1 folds and test this parameter value on the held-out fold.



Cross-Validation

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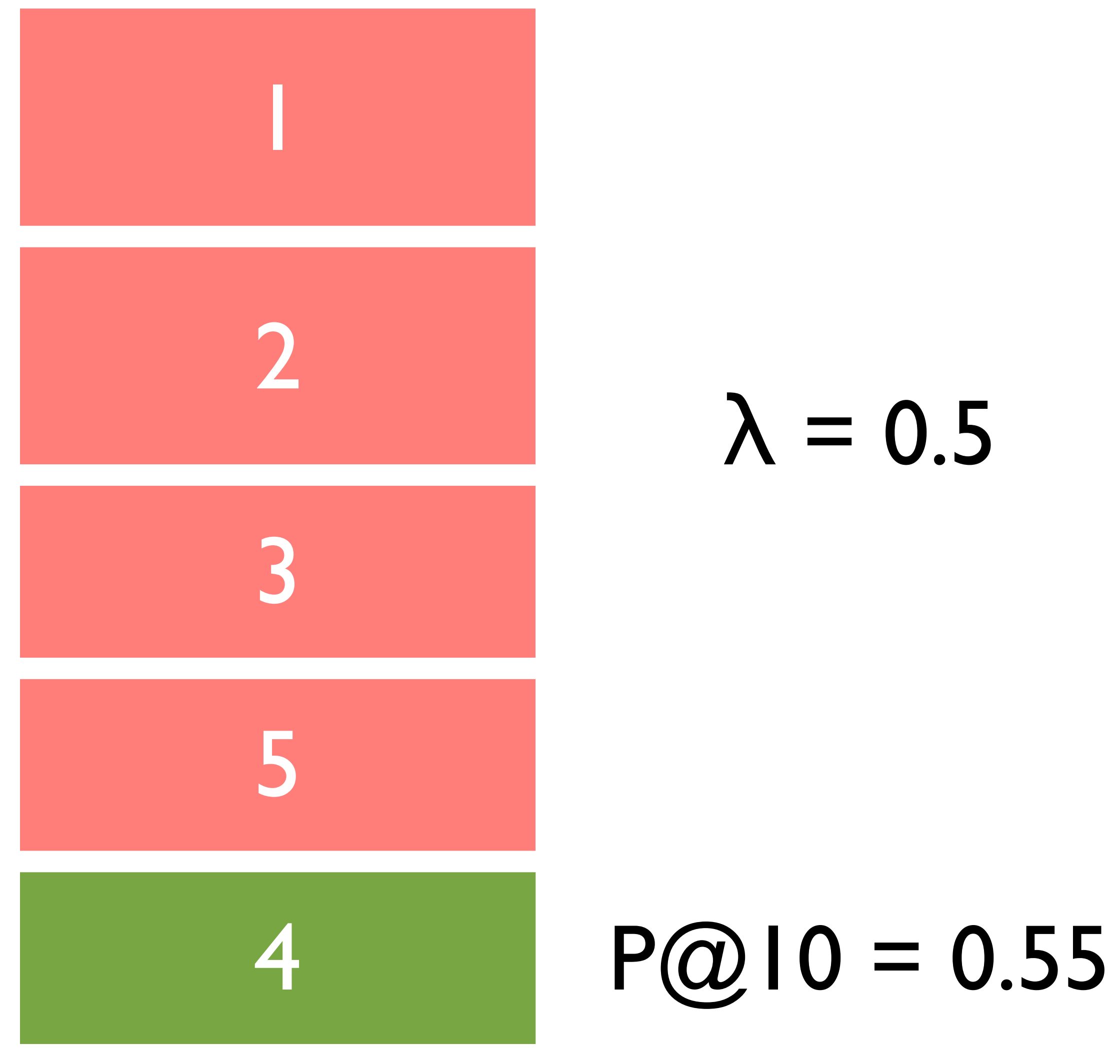

Cross-Validation

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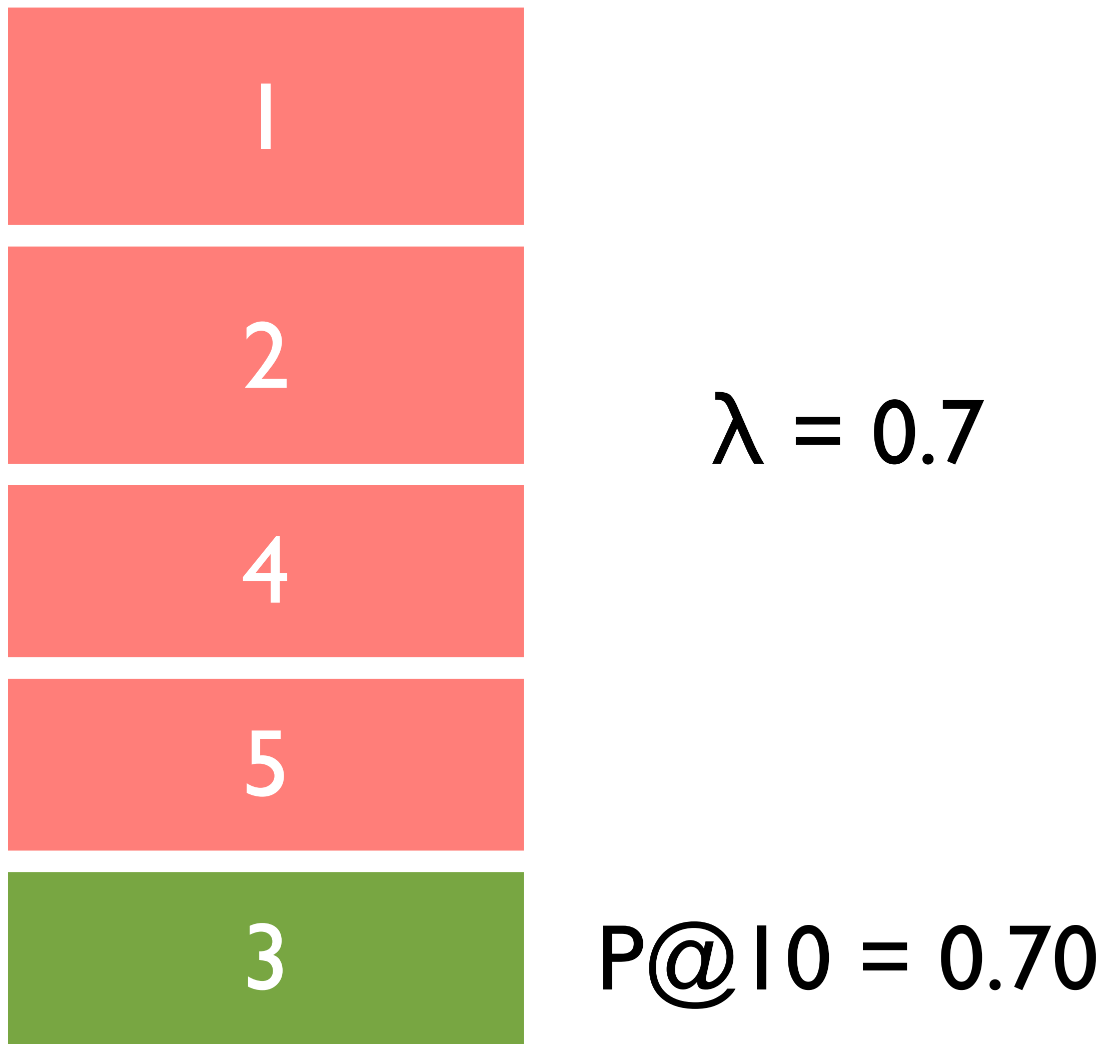

Cross-Validation

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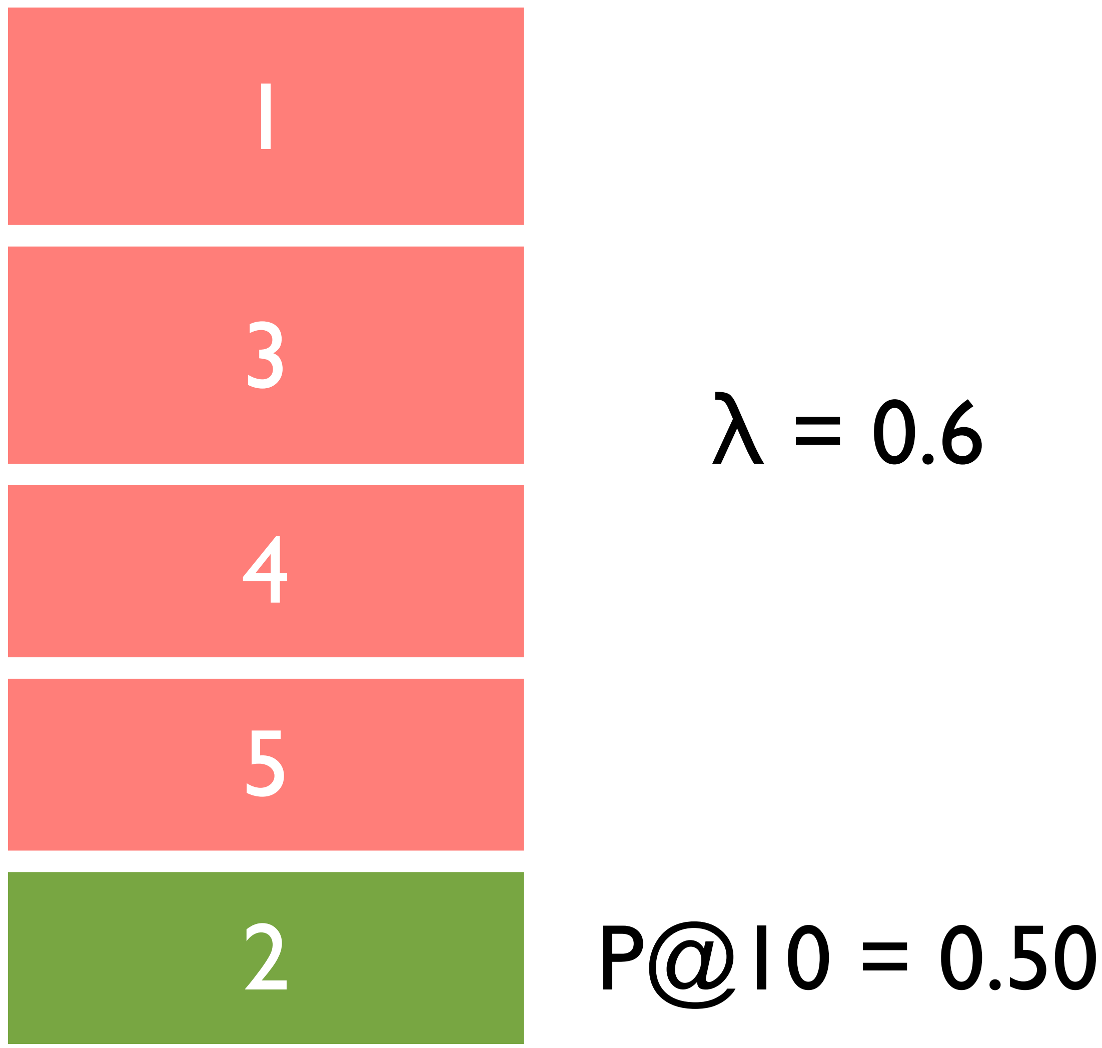
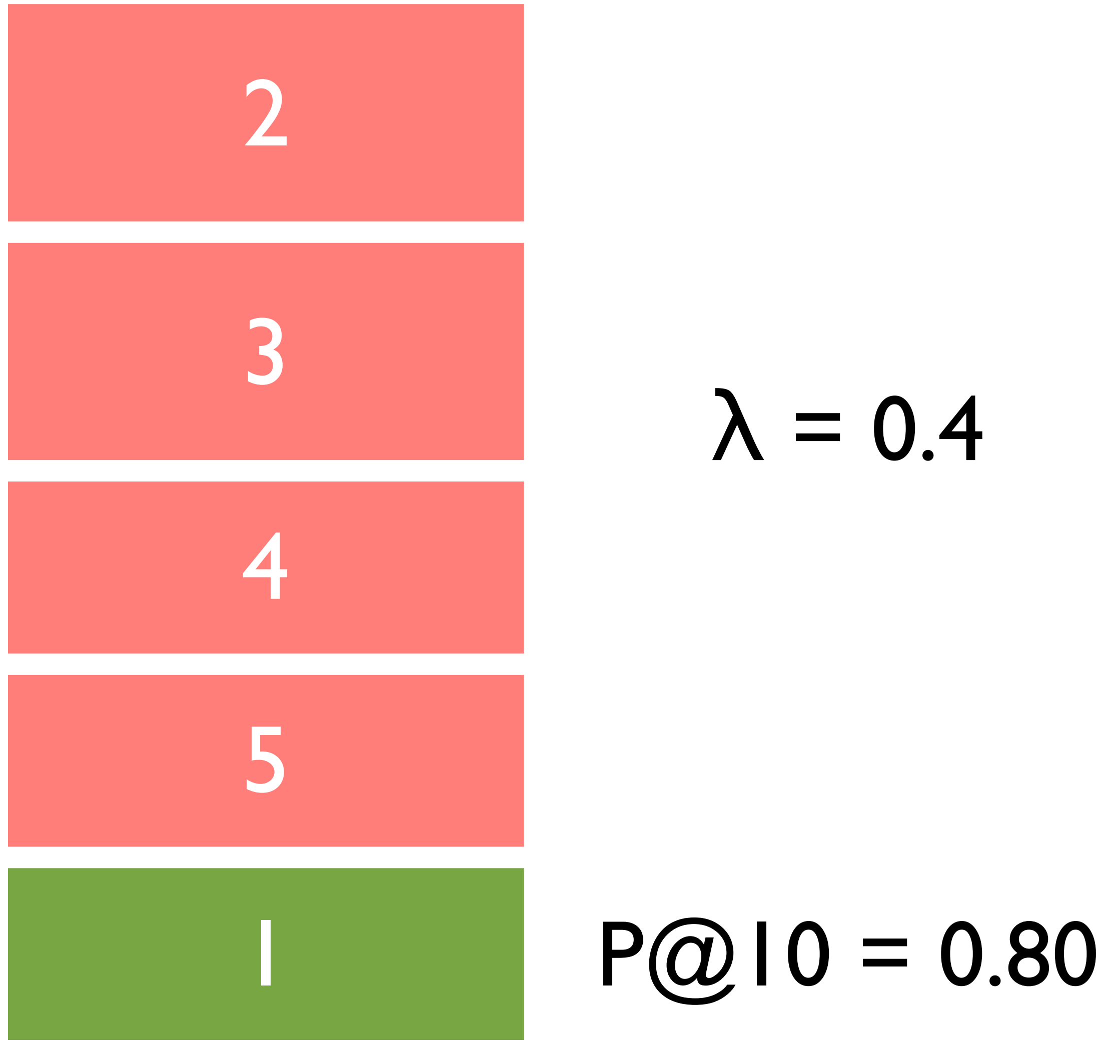


Cross-Validation

- For each fold, find the parameter value that maximizes average performance on the union of N - 1 folds and test this parameter value on the held-out fold.



Cross-Validation

- Average the performance across held-out folds

1	P@10 = 0.80
2	P@10 = 0.50
3	P@10 = 0.70
4	P@10 = 0.55
5	P@10 = 0.50
Average	**P@10 = 0.61**

Cross-Validation

- Average the performance across held-out folds

1	P@10 = 0.80
2	P@10 = 0.50
3	P@10 = 0.70
4	P@10 = 0.55
5	P@10 = 0.50
Average	**P@10 = 0.61**

Advantages and Disadvantages?

N-Fold Cross-Validation

- Advantage
  - multiple rounds of generalization performance.
- Disadvantage
  - ultimately, we'll tune parameters on the set of 50 queries and send our system into the world.
  - a model trained on 50 queries should perform better than one trained on 40.
  - thus, we may be underestimating the model's performance!

Significance Tests

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Outline

Parameter Tuning

Cross-validation

Significance testing

Comparing Between Systems

- The main goal in experimental IR is to develop retrieval techniques that are better than the state of the art and to understand why they are better
- Basic question: Is system B better than system A?
- More often: Is system A with 'special sauce' better than system A without 'special sauce'?

Comparing Systems
P@10

- For each system, tune and test the necessary parameters using N-fold cross-validation
- Use the same folds for both systems
- Compare the difference in average performance across held out folds using a significance test

Fold	System A	System B
1	0.20	0.50
2	0.30	0.30
3	0.10	0.10
4	0.40	0.40
5	1.00	1.00
6	0.80	0.90
7	0.30	0.10
8	0.10	0.20
9	0.00	0.50
10	0.90	0.80
Average	0.41	0.48
	Difference	0.07

Significance Tests
motivation

- Why would it be risky to conclude that System B is better System A based on P@10?
- Put differently, what is it that we're trying to achieve?

Significance Tests

motivation

Significance Tests
motivation

- In theory: the average performance of System B is greater than the average performance of System A for all possible queries!
- However, we don't have all queries. We have a sample (usually about 50).
- And, this sample may favor one system vs. the other!

Significance Tests

definition

- A significance test is a statistical tool that allows us to determine whether a difference in performance reflects a true pattern or just random chance

Significance Tests
ingredients

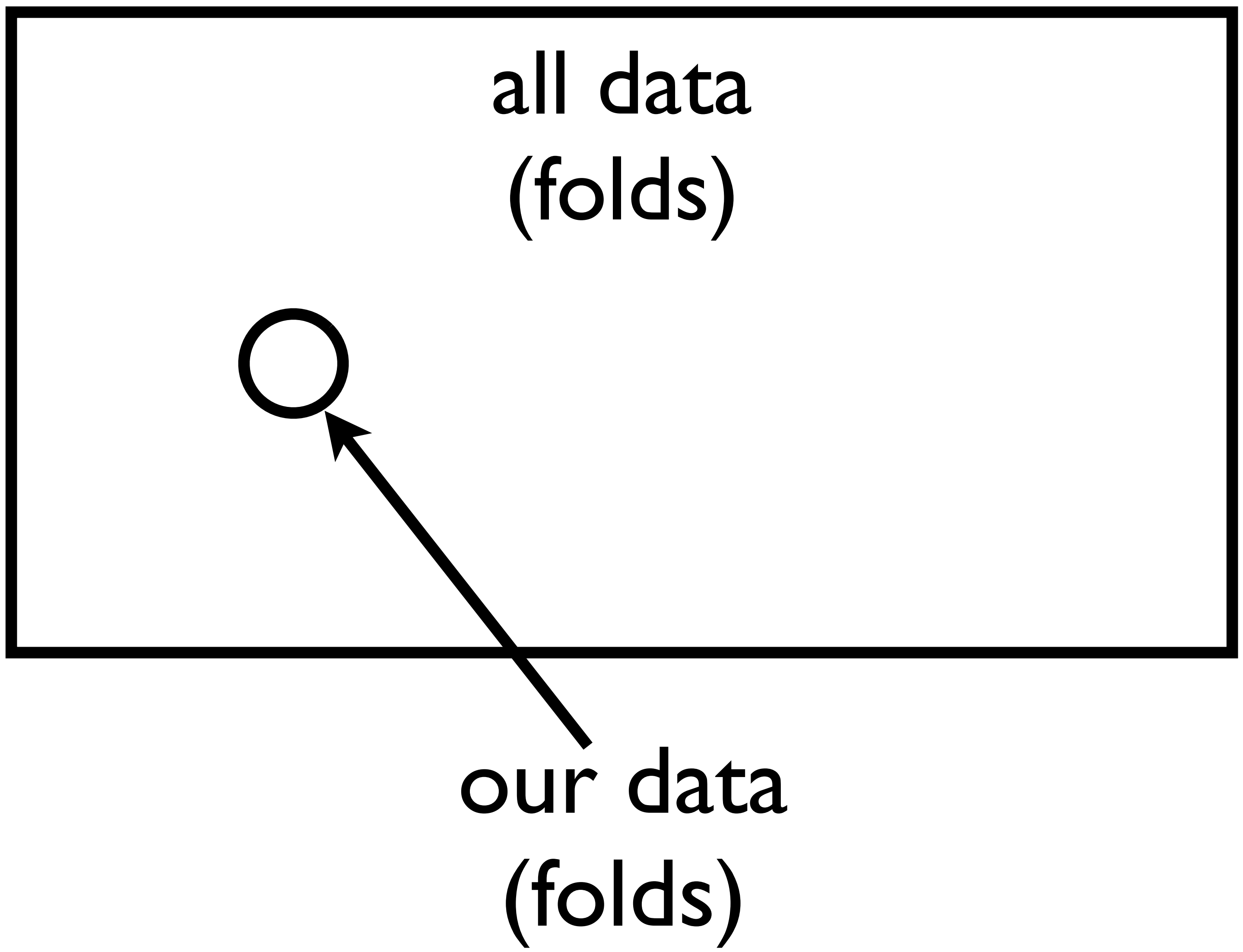
- Test statistic: a measure used to judge the two systems (e.g., the difference between their average P@10 values)
- Null hypothesis: no "true" difference between the two systems
- P-value: take the value of the observed test statistic and compute the probability of observing a value that large (or larger) under the null hypothesis

Significance Tests
ingredients

- If the p-value is large, we cannot reject the null hypothesis
- That is, we cannot claim that one system is better than the other
- There is a high probability that the observed test statistic is due to random chance
- If the p-value is small ($p<0.05$), we can reject the null hypothesis
- That is, we can claim that the observed test-statistic is not due to random chance

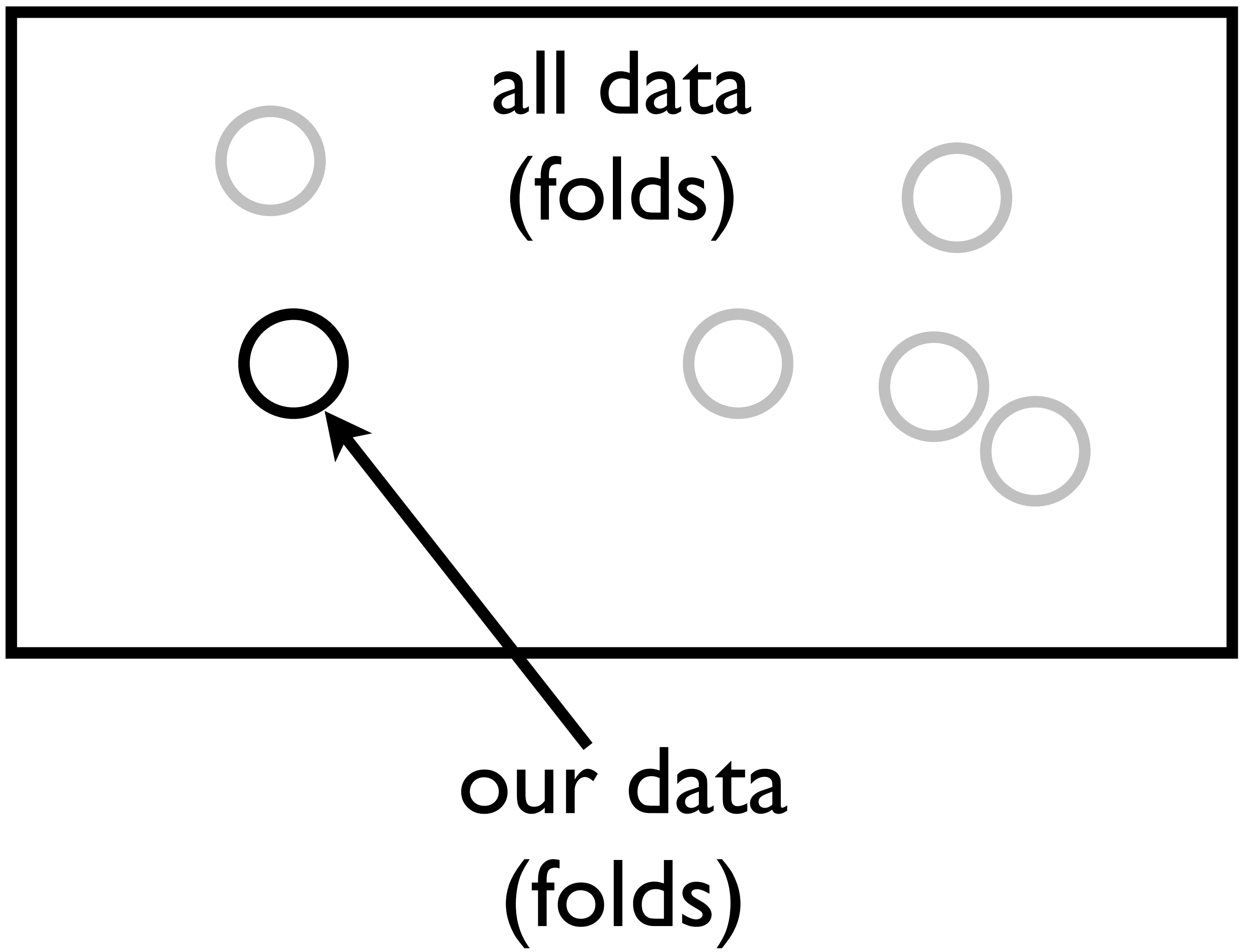
Bootstrap-Shift Test
motivation

- Our sample is a representative sample of all data



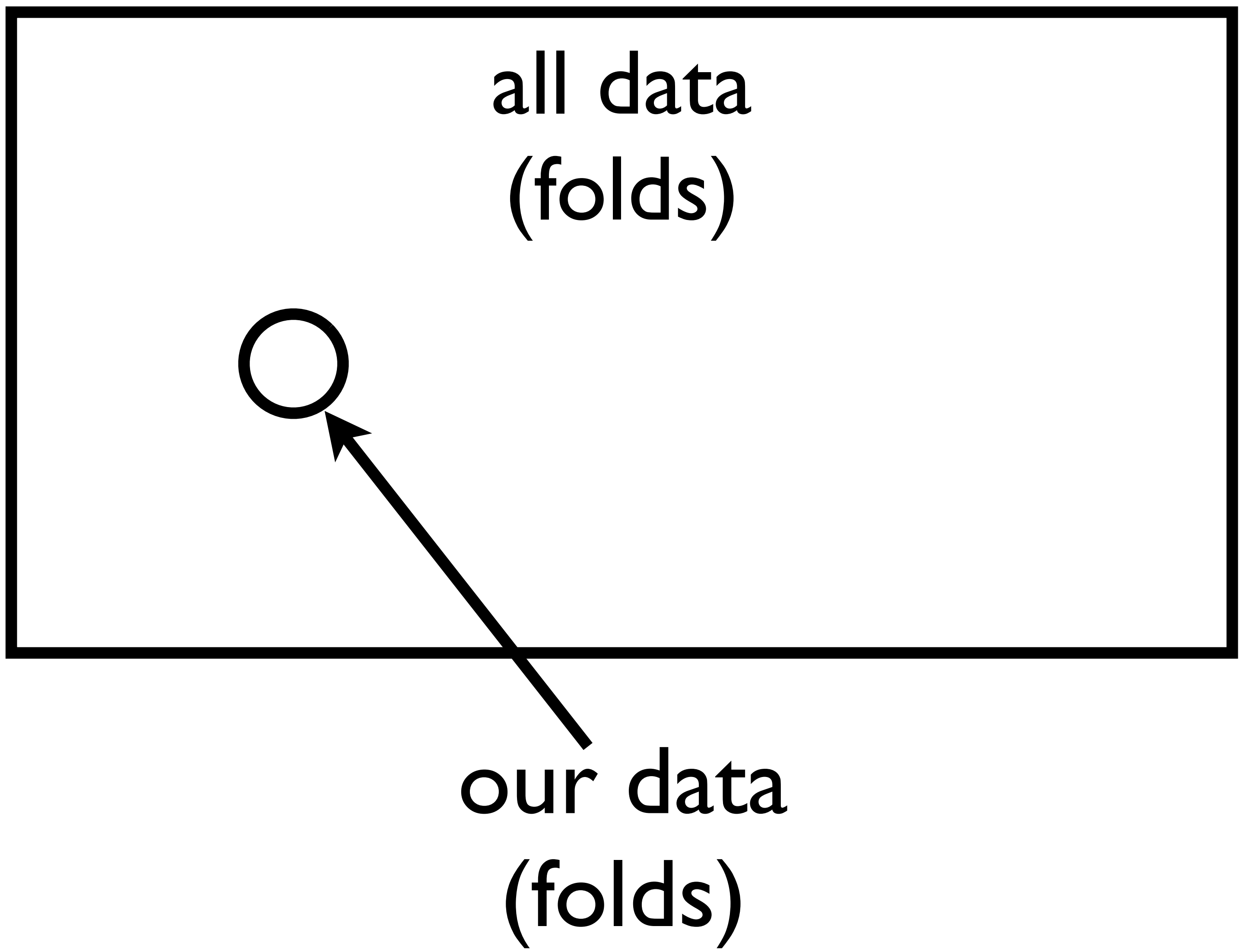
Bootstrap-Shift Test
motivation

- Suppose we could sample many other folds.
- Assuming that the null hypothesis is true, what would be the average test statistic value across all those folds?



Bootstrap-Shift Test
motivation

- If we sample (with replacement) from our sample, we can generate a new representative sample of all data



Bootstrap-Shift Test

procedure

- **Inputs:** Array T = {}, N = 100,000
- Repeat N times:

  Step 1: sample 10 folds (with replacement) from our set of 10 folds (called a subsample)

  Step 2: compute test statistic associated with new sample and add to T
- **Step 3:** compute average of numbers in T
- **Step 4:** reduce every number in T by average
- **Output:** % of numbers in T' greater than or equal to the observed test statistic

Bootstrap-Shift Test

Fold	System A	System B
1	0.20	0.50
2	0.30	0.30
3	0.10	0.10
4	0.40	0.40
5	1.00	1.00
6	0.80	0.90
7	0.30	0.10
8	0.10	0.20
9	0.00	0.50
10	0.90	0.80
Average	0.41	0.48
	Difference	0.07

Bootstrap-Shift Test

Fold	System A	System B	sample
1	0.20	0.50	**0**
2	0.30	0.30	**1**
3	0.10	0.10	**2**
4	0.40	0.40	**2**
5	1.00	1.00	**0**
6	0.80	0.90	**1**
7	0.30	0.10	**1**
8	0.10	0.20	**1**
9	0.00	0.50	**2**
10	0.90	0.80	**0**

iteration = 1

Bootstrap-Shift Test

Fold	System A	System B
2	0.30	0.30
3	0.10	0.10
3	0.10	0.10
4	0.40	0.40
4	0.40	0.40
6	0.80	0.90
7	0.30	0.10
8	0.10	0.20
9	0.00	0.50
9	0.00	0.50
Average	0.25	0.35
	Difference	**0.1**

T = {**0.10**}

iteration = 1

Bootstrap-Shift Test

Fold	System A	System B	**sample**
1	0.20	0.50	**0**
2	0.30	0.30	**0**
3	0.10	0.10	**3**
4	0.40	0.40	**2**
5	1.00	1.00	**0**
6	0.80	0.90	**1**
7	0.30	0.10	**1**
8	0.10	0.20	**1**
9	0.00	0.50	**1**
10	0.90	0.80	**1**

T = {**0.10**}

iteration = 2

Bootstrap-Shift Test

Fold	System A	System B
3	0.10	0.10
3	0.10	0.10
3	0.10	0.10
4	0.40	0.40
4	0.40	0.40
6	0.80	0.90
7	0.30	0.10
8	0.10	0.20
9	0.00	0.50
10	0.90	0.80
Average	0.32	0.36
	Difference	**0.04**

T = {**0.10**, **0.04**}

iteration = 2

Bootstrap-Shift Test

Fold	System A	System B
1	0.20	0.50
1	0.20	0.50
4	0.40	0.40
4	0.40	0.40
4	0.40	0.40
6	0.80	0.90
7	0.30	0.10
8	0.10	0.20
8	0.10	0.20
10	0.90	0.80
Average	0.38	0.44
	Difference	**0.06**

iteration = 100,000

T = {**0.10**,
0.04,
……,
0.06}

Bootstrap-Shift Test

procedure

- **Inputs:** Array T = {}, N = 100,000
- Repeat N times:

  Step 1: sample 10 folds (with replacement) from our set of 10 folds (called a subsample)

  Step 2: compute test statistic associated with new sample and add to T

- **Step 3:** compute average of numbers in T
- **Step 4:** reduce every number in T by average
- **Output:** % of numbers in T' greater than or equal to the observed test statistic

Bootstrap-Shift Test

procedure

- For the purpose of this example, let's assume N = 10.

T = {**0.10**, **0.04**, **0.21**, **0.20**, **0.13**, **0.09**, **0.22**, **0.07**, **0.03**, **0.11**}

Step 3

Average = **0.12**

Step 4

T'= {**-0.02**, **-0.08**, **0.09**, **0.08**, **0.01**, **-0.03**, **0.10**, **-0.05**, -**0.09**, **-0.01**}

Bootstrap-Shift Test
procedure

- **Inputs:** Array T = {}, N = 100,000
- Repeat N times:

  Step 1: sample 10 folds (with replacement) from our set of 10 folds (called a subsample)

  Step 2: compute test statistic associated with new sample and add to T

- **Step 3:** compute <u>average</u> of numbers in T
- **Step 4:** reduce every number in T by <u>average</u>
- **Output:** % of numbers in T' greater than or equal to the observed test statistic

Bootstrap-Shift Test

procedure

- **Output:** (3/10) = **0.30**

T = {**0.10**, **0.04**, **0.21**, **0.20**, **0.13**, **0.09**, **0.22**, **0.07**, **0.03**, **0.11**}

Step 3

Average = **0.12**

Step 4

T'= {**-0.02**, **-0.08**, **0.09**, **0.08**, **0.01**, **-0.03**, **0.10**, **-0.05**, -**0.09**, **-0.01**}

Significance Tests

summary

- Significance tests help us determine whether the outcome of an experiment signals a “true” trend
- The null hypothesis is that the observed outcome is due to random chance (sample bias, error, etc.)
- There are many types of tests
- Parametric tests: assume a particular distribution for the test statistic under the null hypothesis
- Non-parametric tests: make no assumptions about the test statistic distribution under the null hypothesis
- The randomization and bootstrap-shift tests make no assumptions, are robust, and easy to understand