EVALUATION

David Kauchak
CS 158 – Fall 2023

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Admin

Assignment 3

- Autograder

Reading

Mentor hours this week: Thursday and Sunday, 7-9pm

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So far…

1. Throw out outlier examples
2. Remove noisy features
3. Pick "good" features
4. Normalize feature values
   1. center data
   2. scale data (either variance or absolute)
5. Normalize example length
6. Finally, train your model!

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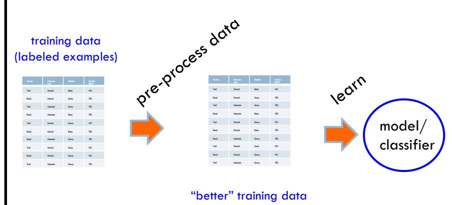
What about testing?



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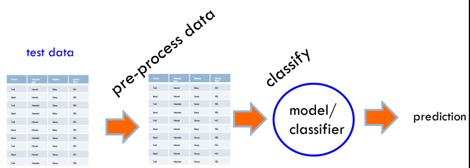
What about testing?



How do we preprocess the test data?

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Test data preprocessing

1. Throw out outlier examples
2. Remove noisy features
3. Pick "good" features
4. Normalize feature values
   1. center data
   2. scale data (either variance or absolute)
5. Normalize example length

Which of these do we need to do on test data?
Any issues?

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Test data preprocessing

1. ~~Throw out outlier examples~~
2. Remove irrelevant/noisy features — Remove/pick same features
3. Pick "good" features
4. Normalize feature values — Do these
   1. center data
   2. scale data (either variance or absolute) — Do this
5. Normalize example length

Whatever you do on training, you have to do the EXACT same on testing!

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Normalizing test data

For each feature (over all examples):

Center: adjust the values so that the mean of that feature is 0: subtract the mean from all values

Rescale/adjust feature values to avoid magnitude bias:

- Variance scaling: divide each value by the std dev
- Absolute scaling: divide each value by the largest value

What values do we use when normalizing testing data?

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Normalizing test data

For each feature (over all examples):

Center: adjust the values so that the mean of that feature is 0: subtract the mean from all values

Rescale/adjust feature values to avoid magnitude bias:

- Variance scaling: divide each value by the std dev
- Absolute scaling: divide each value by the largest value

Save these from training normalization!

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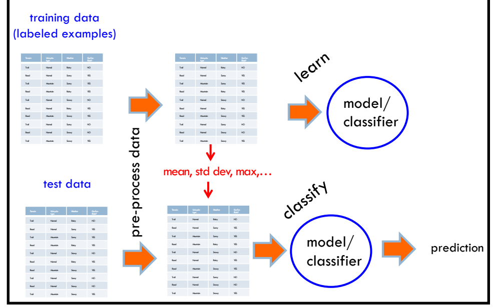
Normalizing test data



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Features pre-processing summary

Many techniques for preprocessing data

Which ones will work well will depend on the data and the classifier

Try them out and evaluate how they affect performance on dev data

Make sure to do the **exact same** pre-processing on train and test

1. Throw out outlier examples
2. Remove noisy features
3. Pick "good" features
4. Normalize feature values
   1. center data
   2. scale data (either variance or absolute)
5. Normalize example length

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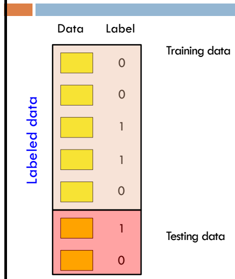
Supervised evaluation



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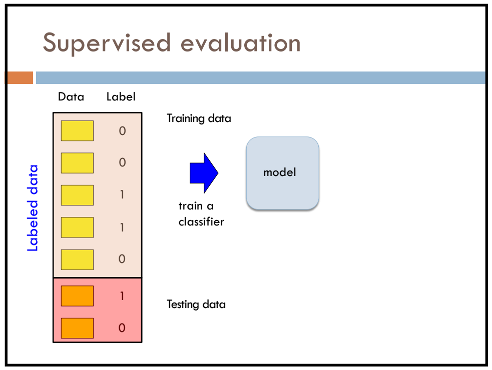
Supervised evaluation
Data
Label
Labeled data
0
0
1
1
0
1
0
Training data
train a
classifier
model
Testing data

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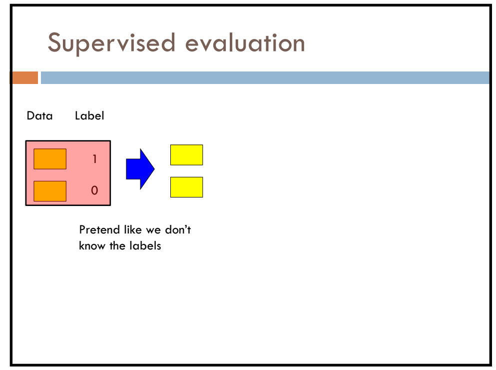
Supervised evaluation
Data
Label
1
0
Pretend like we don't
know the labels

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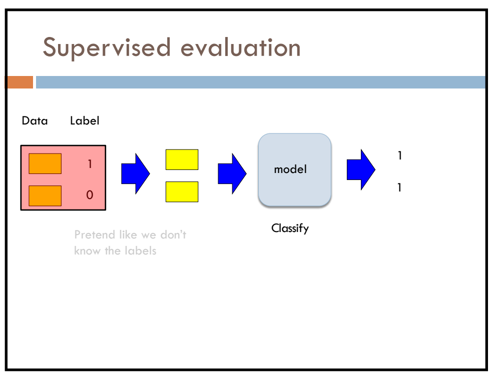
Supervised evaluation
Data
Label
1
0
model
1
1
Pretend like we don't
know the labels
Classify

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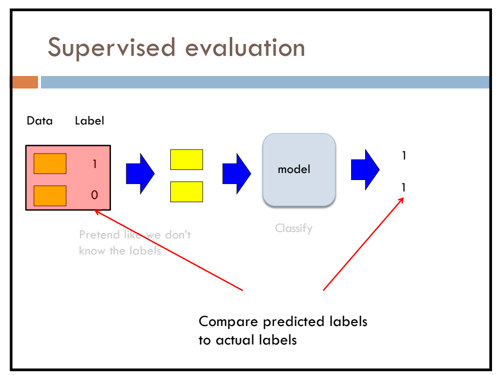
Supervised evaluation
Data
Label
1
0
model
1
1
Pretend like we don't
know the labels
Classify
Compare predicted labels
to actual labels

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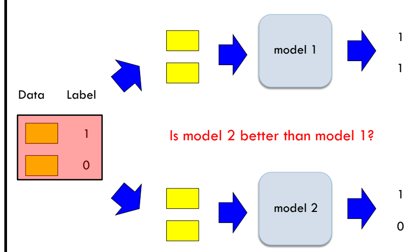
Comparing algorithms



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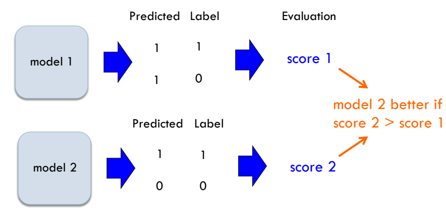
Idea 1



When would we want to do this type of comparison?

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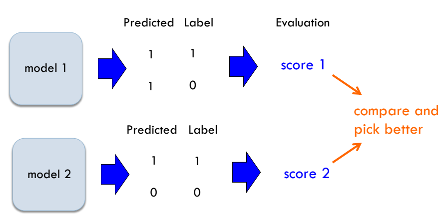
Idea 1



Any concerns?

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Is model 2 better?

Model 1: 85% accuracy
Model 2: 80% accuracy

Model 1: 85.5% accuracy
Model 2: 85.0% accuracy

Model 1: 0% accuracy
Model 2: 100% accuracy

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Comparing scores: significance

Just comparing scores on one data set isn't enough!

We don't just want to know which system is better on ***this particular data***, we want to know if model 1 is better than model 2 ***in general***

Put another way, we want to be confident that the difference is real and not just due to chance or eccentricities about the particular dataset

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Idea 2

	Predicted	Label		Evaluation
model 1	1	1		score 1
	1	0		

model 2 better if
score 2 + c > score 1

	Predicted	Label		
model 2	1	1		score 2
	0	0		

Is this any better?

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Idea 2

	Predicted	Label		Evaluation
model 1	1	1		score 1
	1	0		

model 2 better if
score 2 + c > score 1

	Predicted	Label		
model 2	1	1		score 2
	0	0		

NO!
Key: we don't know the variance of the output

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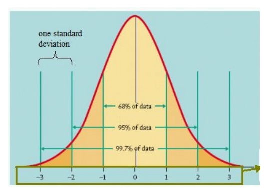
Variance

Recall that variance (or standard deviation) helped us predict how likely certain events are:



How do we know how variable a model's accuracy is?

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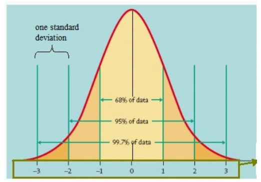
Variance

Recall that variance (or standard deviation) helped us predict how likely certain events are:



We need multiple accuracy scores! Ideas?

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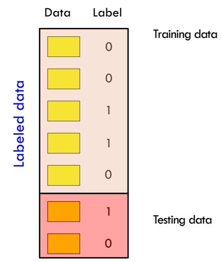
Repeated experimentation



Rather than just splitting once, split multiple times

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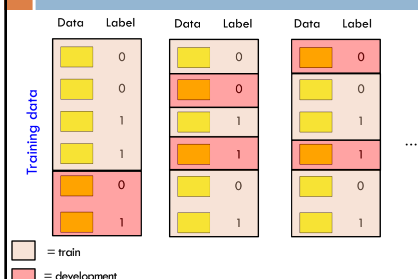
Repeated experimentation



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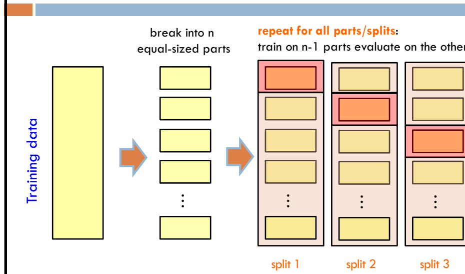
n-fold cross validation



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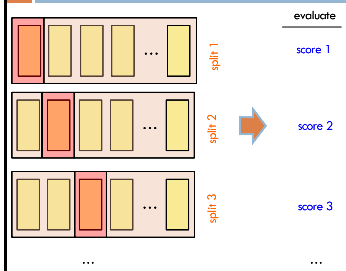
n-fold cross validation



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n-fold cross validation

better utilization of labeled data

more robust: doesn't just rely on one test/development set to evaluate the approach (or for optimizing parameters)

multiplies the computational overhead by *n* (have to train *n* models instead of just one)

10 is the most common choice of *n*

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Leave-one-out cross validation

n-fold cross validation where *n* = number of examples

aka "jackknifing"

pros/cons?

when would we use this?

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Leave-one-out cross validation

Can be very expensive if training is slow and/or if there are a large number of examples

Useful in domains with limited training data: *maximizes the data we can use for training*

Some classifiers are very amenable to this approach (e.g.?)

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Random splits

n-fold cross-validation explicitly divides the data into *n* partitions and each data point gets used exactly once for testing

Another approach is do some number of random X/Y splits (like we did on Assignment 2)

Pros/cons?

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Random splits

Lose the guarantee that all examples are used once for testing

Can be slower (if we do more splits)

Can allow for more samples

Both are fine approaches!

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Comparing systems: sample 1

split	model 1	model 2
1	87	88
2	85	84
3	83	84
4	80	79
5	88	89
6	85	85
7	83	81
8	87	86
9	88	89
10	84	85
average:	**85**	**85**

Is model 2 better than model 1?

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Comparing systems: sample 2

split	model 1	model 2
1	87	87
2	92	88
3	74	79
4	75	86
5	82	84
6	79	87
7	83	81
8	83	92
9	88	81
10	77	85
average:	**82**	**85**

Is model 2 better than model 1?

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Comparing systems: sample 3

split	model 1	model 2
1	84	87
2	83	86
3	78	82
4	80	86
5	82	84
6	79	87
7	83	84
8	83	86
9	85	83
10	83	85
average:	**82**	**85**

Is model 2 better than model 1?

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Comparing systems

split	model 1	model 2
1	84	87
2	83	86
3	78	82
4	80	86
5	82	84
6	79	87
7	83	84
8	83	86
9	85	83
10	83	85
average:	**82**	**85**

split	model 1	model 2
1	87	87
2	92	88
3	74	79
4	75	86
5	82	84
6	79	87
7	83	81
8	83	92
9	88	81
10	77	85
average:	**82**	**85**

What's the difference?

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Comparing systems

split	model 1	model 2
1	84	87
2	83	86
3	78	82
4	80	86
5	82	84
6	79	87
7	83	84
8	83	86
9	85	83
10	83	85
average:	**82**	**85**
std dev	**2.3**	**1.7**

split	model 1	model 2
1	87	87
2	92	88
3	74	79
4	75	86
5	82	84
6	79	87
7	83	81
8	83	92
9	88	81
10	77	85
average:	**82**	**85**
std dev	**5.9**	**3.9**

Even though the averages are same, the variance is different!

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Comparing systems: sample 4

split	model 1	model 2
1	80	82
2	84	87
3	89	90
4	78	82
5	90	91
6	81	83
7	80	80
8	88	89
9	76	77
10	86	88
average:	**83**	**85**
std dev	**4.9**	**4.7**

Is model 2 better than model 1?

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Comparing systems: sample 4

split	model 1	model 2	model 2 – model 1
1	80	82	2
2	84	87	3
3	89	90	1
4	78	82	4
5	90	91	1
6	81	83	2
7	80	80	0
8	88	89	1
9	76	77	1
10	86	88	2
average:	**83**	**85**	
std dev	**4.9**	**4.7**	

Is model 2 better than model 1?

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Comparing systems: sample 4

split	model 1	model 2	model 2 – model 1
1	80	82	2
2	84	87	3
3	89	90	1
4	78	82	4
5	90	91	1
6	81	83	2
7	80	80	0
8	88	89	1
9	76	77	1
10	86	88	2
average:	**83**	**85**	
std dev	**4.9**	**4.7**	

Model 2 is ALWAYS better

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Comparing systems: sample 4

split	model 1	model 2	model 2 – model 1
1	80	82	2
2	84	87	3
3	89	90	1
4	78	82	4
5	90	91	1
6	81	83	2
7	80	80	0
8	88	89	1
9	76	77	1
10	86	88	2
average:	**83**	**85**	
std dev	**4.9**	**4.7**	

How do we decide if model 2 is better than model 1?

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Statistical tests

Setup:

- Assume some default hypothesis about the data that you'd like to *disprove*, called the null hypothesis
- e.g. model 1 and model 2 are not statistically different in performance

Test:

- Calculate a test statistic from the data (often assuming something about the data)
- Based on this statistic, with *some probability* we can **reject the null hypothesis,** that is, show that it does not hold

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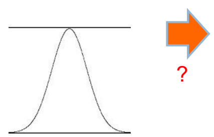
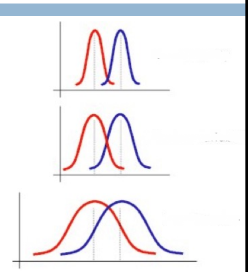
t-test

Determines whether two samples come from the same underlying distribution or not





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t-test

Null hypothesis: model 1 and model 2 accuracies are no different, i.e. come from **the same** distribution

Assumptions: there are a number that often aren't completely true, but we're often not too far off

Result: probability that the difference in accuracies is due to random chance (low values are better)

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Calculating t-test

For our setup, we'll do what's called a "paired t-test"

- The values can be thought of as pairs, where they were calculated under the same conditions
- In our case, the same train/test split
- Gives more power than the unpaired t-test (we have more information)

For almost all experiments, we'll do a "two-tailed" version of the t-test

Can calculate by hand or in code, but why reinvent the wheel: use excel or a statistical package

http://en.wikipedia.org/wiki/Student's_t-test

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p-value

The result of a statistical test is often a p-value

p-value: the probability that the null hypothesis holds. Specifically, if we re-ran this experiment multiple times (say on different data) what is the probability that we would reject the null hypothesis incorrectly (i.e. the probability we'd be wrong)

Common values to consider "significant": 0.05 (95% confident), 0.01 (99% confident) and 0.001 (99.9% confident)

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Comparing systems: sample 1

split	model 1	model 2
1	87	88
2	85	84
3	83	84
4	80	79
5	88	89
6	85	85
7	83	81
8	87	86
9	88	89
10	84	85
average:	**85**	**85**

Is model 2 better than model 1?

They are the same with: p = 1

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Comparing systems: sample 2

split	model 1	model 2
1	87	87
2	92	88
3	74	79
4	75	86
5	82	84
6	79	87
7	83	81
8	83	92
9	88	81
10	77	85
average:	**82**	**85**

Is model 2 better than model 1?

They are the same with: p = 0.15

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Comparing systems: sample 3

split	model 1	model 2
1	84	87
2	83	86
3	78	82
4	80	86
5	82	84
6	79	87
7	83	84
8	83	86
9	85	83
10	83	85
average:	**82**	**85**

Is model 2 better than model 1?

They are the same with: p = 0.007

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Comparing systems: sample 4

split	model 1	model 2
1	80	82
2	84	87
3	89	90
4	78	82
5	90	91
6	81	83
7	80	80
8	88	89
9	76	77
10	86	88
average:	**83**	**85**

Is model 2 better than model 1?

They are the same with: p = 0.001

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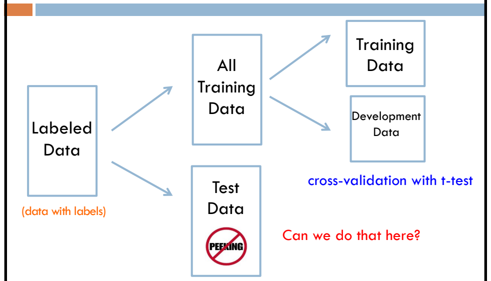
Statistical tests on test data



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Bootstrap resampling

test set *t* with n samples

do *m* times:

- sample *n* examples **with replacement** from the test set to create a new test set *t'*
- evaluate model(s) on *t'*

calculate t-test (or other statistical test) on the collection of *m* results

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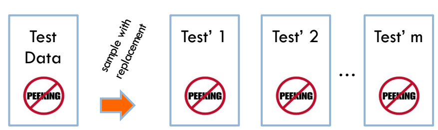
Bootstrap resampling



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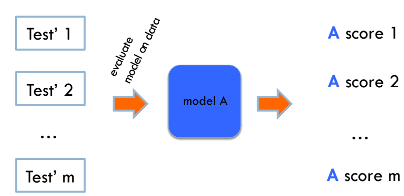
Bootstrap resampling



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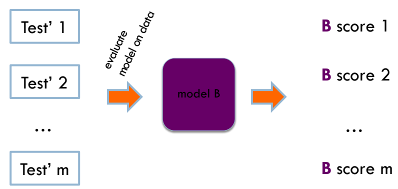
Bootstrap resampling



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Bootstrap resampling

A score 1	**B** score 1
A score 2	**B** score 2
…	…
A score m	**B** score m

paired t-test (or other analysis)

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Experimentation good practices

Never look at your test data!

During development

- Compare different models/hyperparameters on development data
- use cross-validation to get more consistent results
- If you want to be confident with results, use a t-test and look for $p = 0.05$ (or even lower)

For final evaluation, use bootstrap resampling combined with a t-test to compare final approaches

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