Natural Language Processing

Lecture 16

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Goals for Today

- Understand how to robustly **evaluate** results
- Learn how to **improve** performance

Recap: Text Classification

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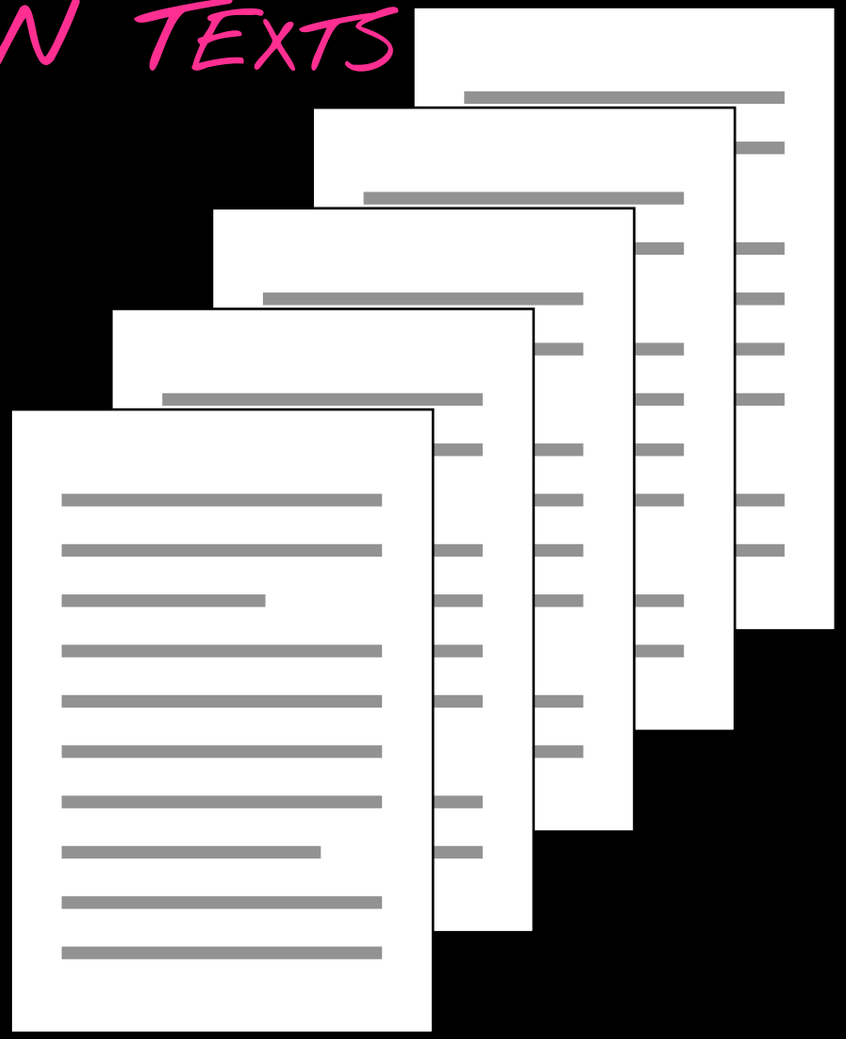
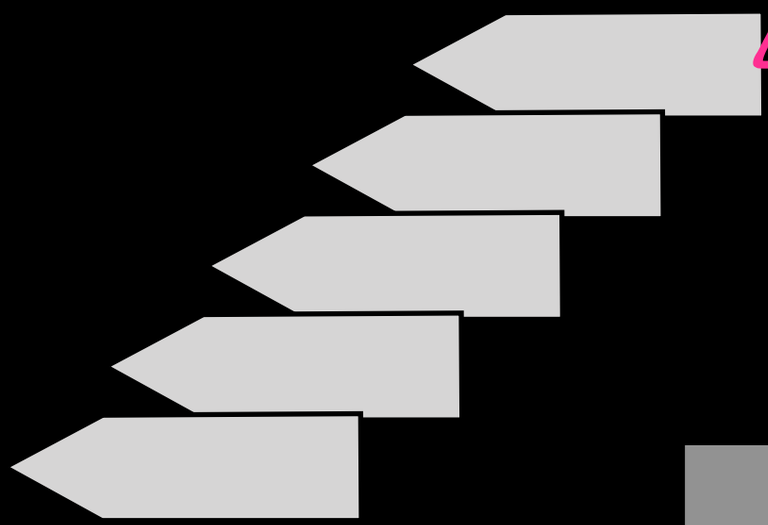
N TEXTS



N-BY-D MATRIX

X

LABELS



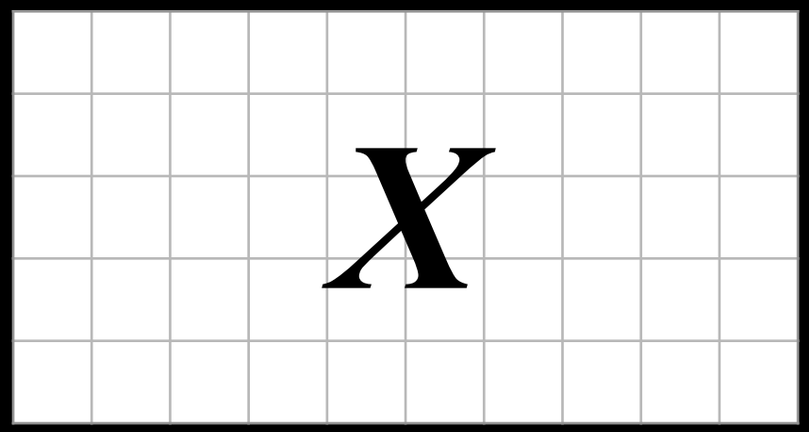
N-BY-1 VECTOR

y

Fitting

$$f(X) = y$$

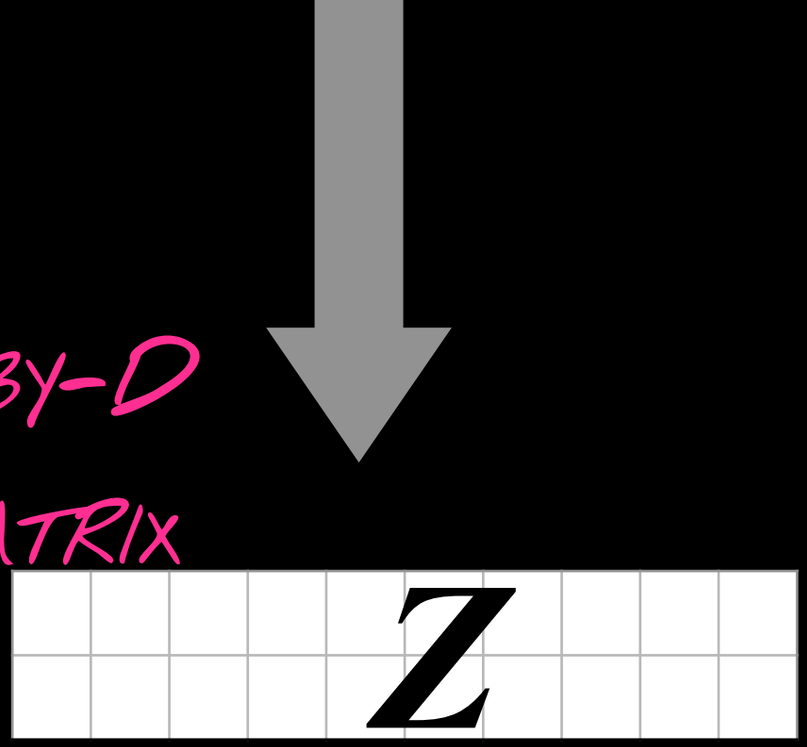
D-BY-1 VECTOR

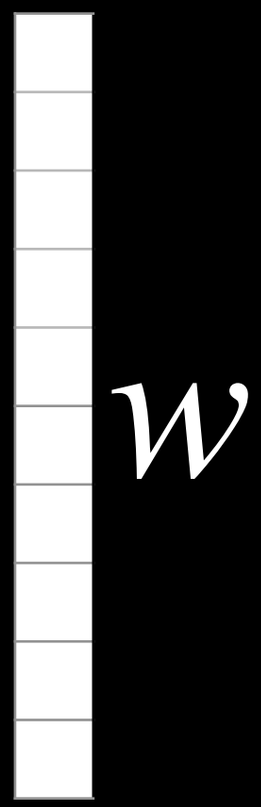


Predicting

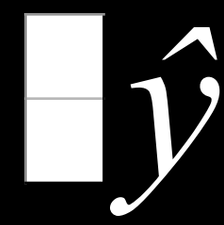
$$f(\boldsymbol{Z}) = \boldsymbol{Z}\, w^T = \hat{y}$$

K-BY-D MATRIX





1-BY-K VECTOR

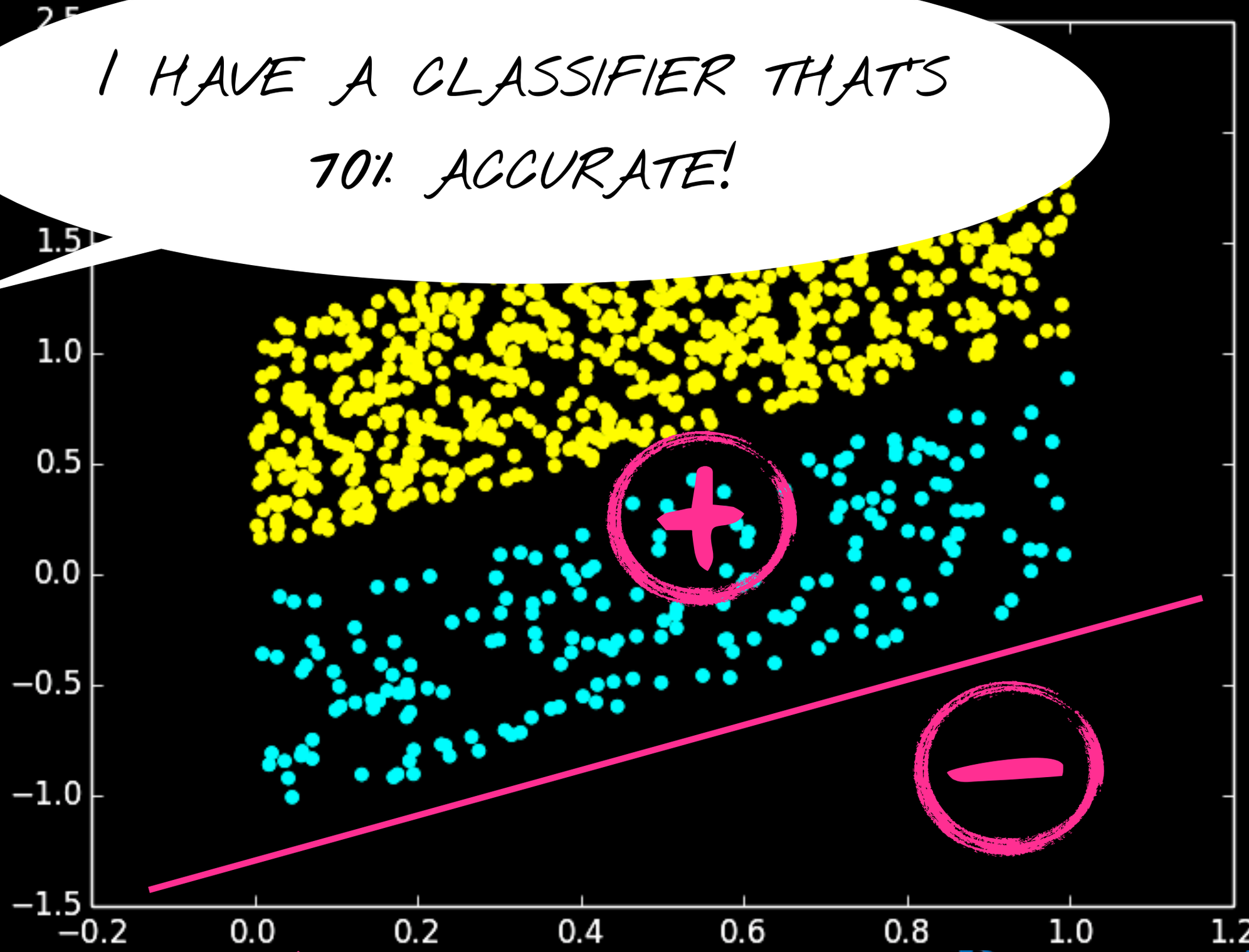


Evaluating Performance

Performance Problems

I HAVE A CLASSIFIER THAT'S 70% ACCURATE!

x	y	ŷ
frog	1	1
deer	1	1
wolf	1	1
dog	1	1
bear	1	1
fish	1	1
bird	1	0
cat	1	0
stone	0	1
tree	0	0



A 70% ACCURATE CLASSIFIER

True and False

		predicted	
		1	0
gold	1	TP	FN
	0	FP	TN

accuracy = (TP+TN) / (P + N)

precision = TP / (TP + FP)

recall = TP / (TP + FN)

F1 = 2 (prec x rec) / (prec + rec)

TARGET = ANIMAL

x	y	ŷ	
frog	1	1	true positive
deer	1	1	
wolf	1	1	
dog	1	1	
bear	1	1	
fish	1	1	
bird	1	0	false negative
cat	1	0	
stone	0	1	false positive
tree	0	0	true negative

ACCURACY = 7/10 = 0.7

PRECISION = 6/7 = 0.86

RECALL = 6/8 = 0.75

F1 = 0.81

Changing Target

		predicted	
		1	0
gold	1	TP	FN
	0	FP	TN

accuracy = (TP+TN) / (P + N)

precision = TP / (TP + FP)

recall = TP / (TP + FN)

F1 = 2 (prec x rec) / (prec + rec)

TARGET = THING

	x	**y**	**ŷ**	
	frog	0	0	
	deer	0	0	
	wolf	0	0	true negative
	dog	0	0	
	bear	0	0	
	fish	0	0	
	bird	0	1	false positive
	cat	0	1	
	stone	1	0	false negative
	tree	1	1	true positive

ACCURACY = 7/10 = 0.7

PRECISION = 1/3 = 0.33

RECALL = 1/2 = 0.5

F1 = 0.4

		predicted	
		1	0
gold	1	TP	FN
	0	FP	TN

MICRO Averaging

WEIGH BY CLASS SIZE

accuracy = (TP+TN) / (P + N)

precision = TP / (TP + FP)

recall = TP / (TP + FN)

F1 = 2 (prec x rec) / (prec + rec)

ANIMAL

x	**y**	**ŷ**
frog	1	1
deer	1	1
wolf	1	1
dog	1	1
bear	1	1
fish	1	1
bird	1	1
cat	1	0
stone	0	1
tree	0	0

THING

x	**y**	**ŷ**
frog	0	0
deer	0	0
wolf	0	0
dog	0	0
bear	0	0
fish	0	0
bird	0	0
cat	0	1
stone	1	0
tree	1	1

ACC = (7+7)/(10+10) = 14/20 = 0.7

PREC = (6+1)/(7+3) = 7/10 = 0.7

REC = (6+1)/(8+2) = 7/10 = 0.7

F1 = 0.7

	predicted		
gold		1	0
	1	TP	FN
	0	FP	TN

MACRO Averaging

WEIGH ALL CLASSES EQUALLY

accuracy = (TP+TN) / (P + N)

precision = TP / (TP + FP)

recall = TP / (TP + FN)

F1 = 2 (prec x rec) / (prec + rec)

ANIMAL

x	**y**	**ŷ**
frog	1	1
deer	1	1
wolf	1	1
dog	1	1
bear	1	1
fish	1	1
bird	1	1
cat	1	0
stone	0	1
tree	0	0

THING

x	**y**	**ŷ**
frog	0	0
deer	0	0
wolf	0	0
dog	0	0
bear	0	0
fish	0	0
bird	0	0
cat	0	1
stone	1	0
tree	1	1

ACC = (0.7 + 0.7) / 2 = 0.7

PREC = (0.86 + 0.33) / 2 = 0.6

REC = (0.5 + 0.75) / 2 = 0.63

F1 = 0.61

Baseline: Total Recall

		predicted	
		1	0
gold	1	TP	FN
	0	FP	TN

PREDICT MAJORITY CLASS FOR ALL

TARGET = ANIMAL

x	y	ŷ
frog	1	1
deer	1	1
wolf	1	1
dog	1	1
bear	1	1
fish	1	1
bird	1	1
cat	1	1
stone	0	1
tree	0	1

true positive

false positive

accuracy = (TP+TN) / (P + N)

precision = TP / (TP + FP)

recall = TP / (TP + FN)

F1 = 2 (prec x rec) / (prec + rec)

ACCURACY = 8/10 = 0.8

PRECISION = 8/10 = 0.8

RECALL = 8/8 = 1.0

F1 = 0.9

Metrics Overview

- **accuracy** can be too general
- **precision** and **recall** are per-class measures
- **precision** = how many of instances labeled as target class are actually *in* target class?
- **recall** = how many of *all* target class instances in data identified correctly?
- **F1** = symmetric mean of precision and recall

Significance Testing

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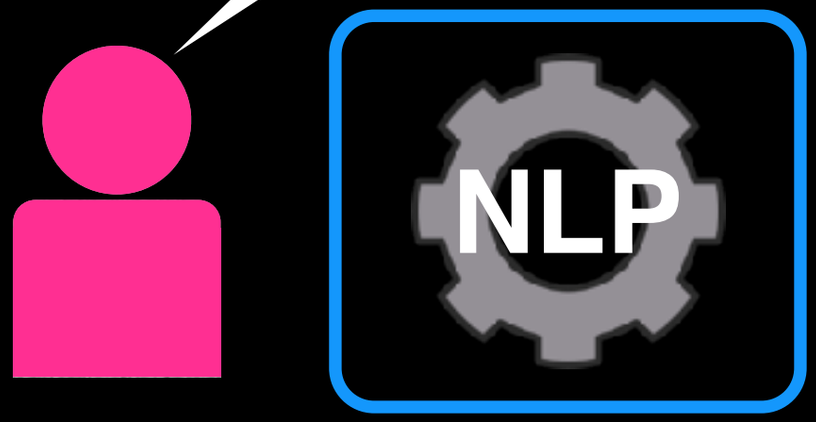
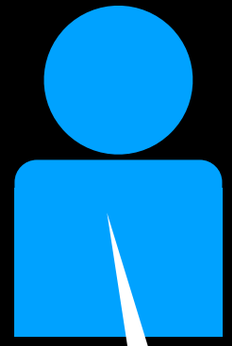
What does a *p*-Value Tell Us?

THIS CLASSIFIER IS 70% ACCURATE! (ON MY DATA SET)





…AND ON MINE?

Bootstrap Sampling

y	$\hat{y}1$		$\hat{y}2$	
1	1	*3/5*	1	*1/5*
1	0		0	
1	1		0	
0	1		1	
0	0		1	

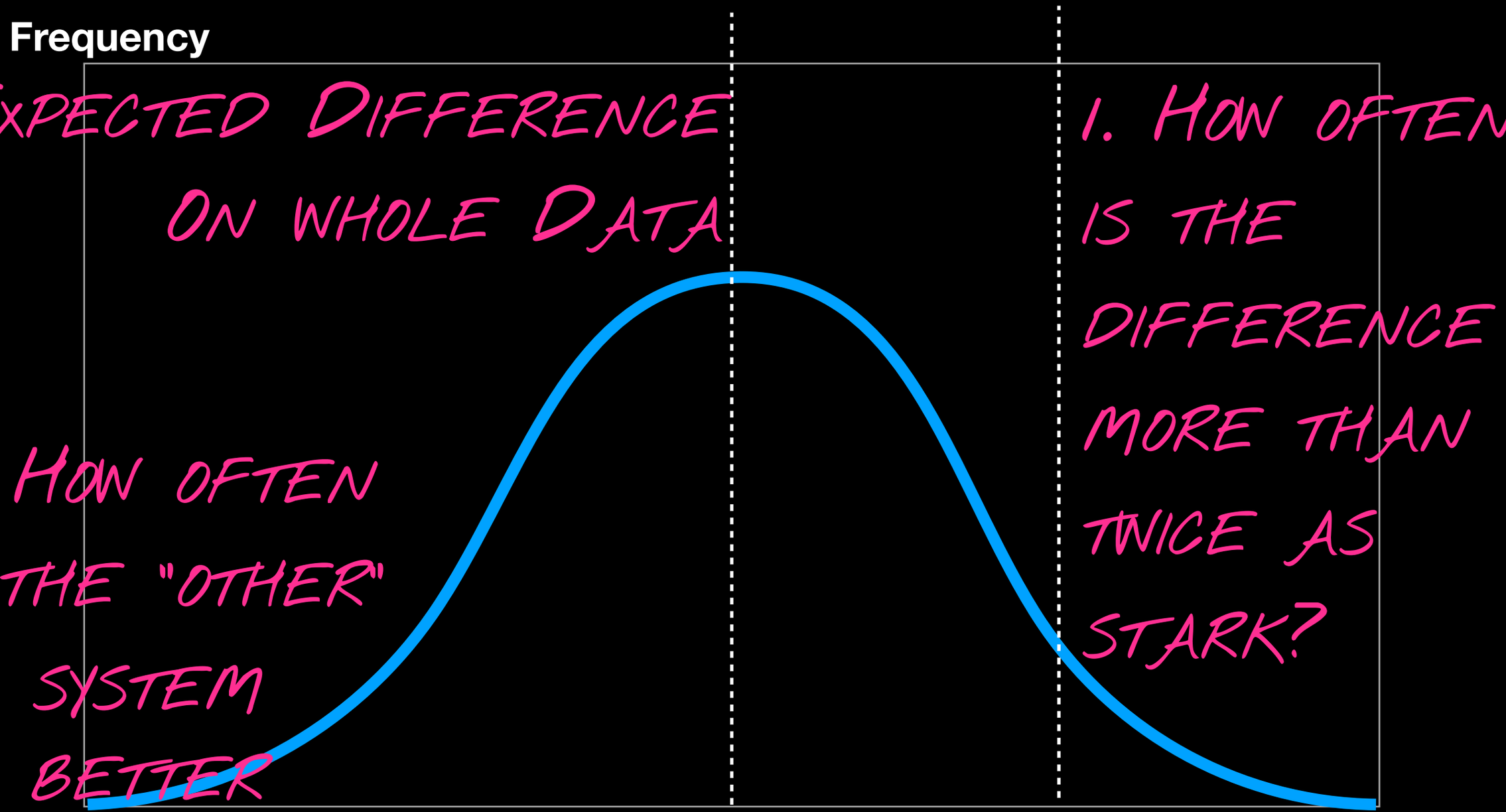
COMPARE ON SUBSETS

1	1	*1/3*	1	*1/3*
1	0		0	
0	1		1	
1	0	*1/3*	0	*0/3*
1	1		0	
0	0		1	
1	1	*2/3*	1	*1/3*
1	1		0	
0	1		1	

Bootstrap Sampling

Sampled Differences follow normal Distro:

Central Limit Theorem



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Bootstrap Sampling

	System 1	System 2	Difference(1-2)
full	**82.13**	**81.89**	**0.24**
1	81.96	82.03	-0.07
2	81.86	82.61	-0.75
3	81.70	81.44	0.26
4	82.42	82.77	-0.35
5	81.89	81.06	0.83
6	81.39	81.24	0.15
7	81.96	81.58	0.37
8	82.57	81.65	0.92
9	82.50	82.67	-0.17
10	83.07	81.84	1.23
		p-value	**0.3**

Note: Significance is Binary!

Cut-offs: 0.1 (meh), 0.05 (standard), 0.01 (strict)

(barely) not statistically significant (p=0.052) a barely detectable statistically significant difference (p=0.073) a borderline significant trend (p=0.09) a certain trend toward significance (p=0.08) a clear tendency to significance (p=0.052) a clear trend (p<0.09) a clear, strong trend (p=0.09) a considerable trend toward significance (p=0.069) a decreasing trend (p=0.09) a definite trend (p=0.08) a distinct trend toward significance (p=0.07) \borderline conventional significance (p=0.051) borderline level of statistical significance (p=0.053)	borderline significant (p=0.09) did not quite reach conventional levels of statistical significance (p=0.079) did not quite reach statistical significance (p=0.063) did not reach the traditional level of significance (p=0.10) did not reach the usually accepted level of clinical significance (p=0.07) difference was apparent (p=0.07) direction heading towards significance (p=0.10) does not appear to be sufficiently significant (p>0.05) does not narrowly reach statistical significance (p=0.06)	does not reach the conventional significance level (p=0.098) effectively significant (p=0.051) equivocal significance (p=0.06) essentially significant (p=0.10) extremely close to significance (p=0.07) failed to reach significance on this occasion (p=0.09) failed to reach statistical significance (p=0.06) fairly close to significance (p=0.065) fairly significant (p=0.09) falls just short of standard levels of statistical significance (p=0.06) fell (just) short of significance (p=0.08)	fell barely short of significance (p=0.08) scarcely significant (0.05<p>0.1) significant at the .07 level significant tendency (p=0.09) significant to some degree (0<p>1) significant, or close to significant effects (p=0.08, p=0.05) significantly better overall (p=0.051) significantly significant (p=0.065) similar but not nonsignificant trends (p>0.05) slight evidence of significance (0.1>p>0.05) slight non-significance (p=0.06) slight significance (p=0.128)

Evaluation Don'ts

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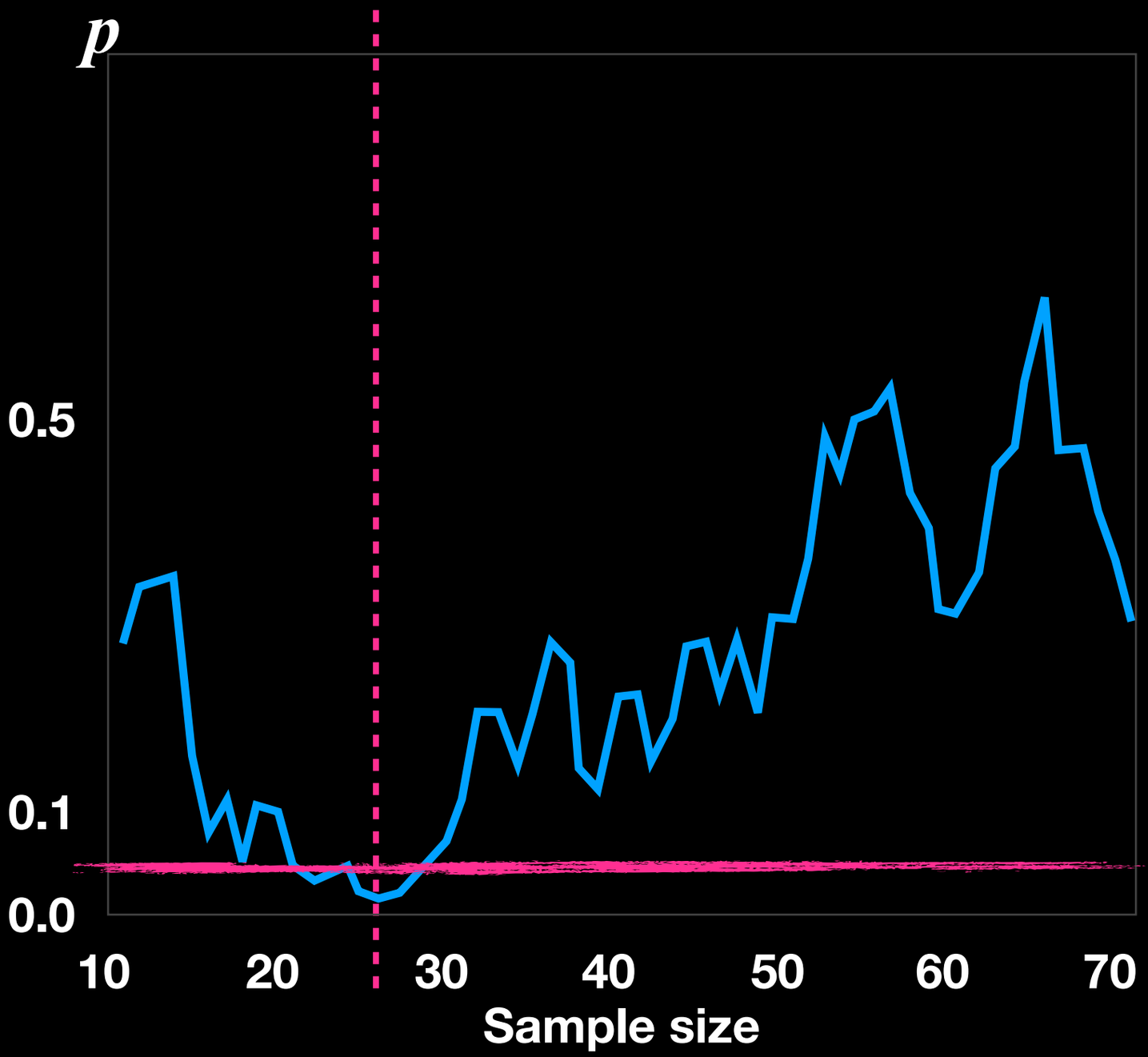
Don’t choose among metrics

metric	p
[illegible]	0,0899
pre[illegible]ion	0,062
re[illegible]ll	0,179
accuracy	0,0014

REPORT!

Don’t choose sample sizes



“We observed significant results at a sample size of 26”

…but not with smaller or larger samples!

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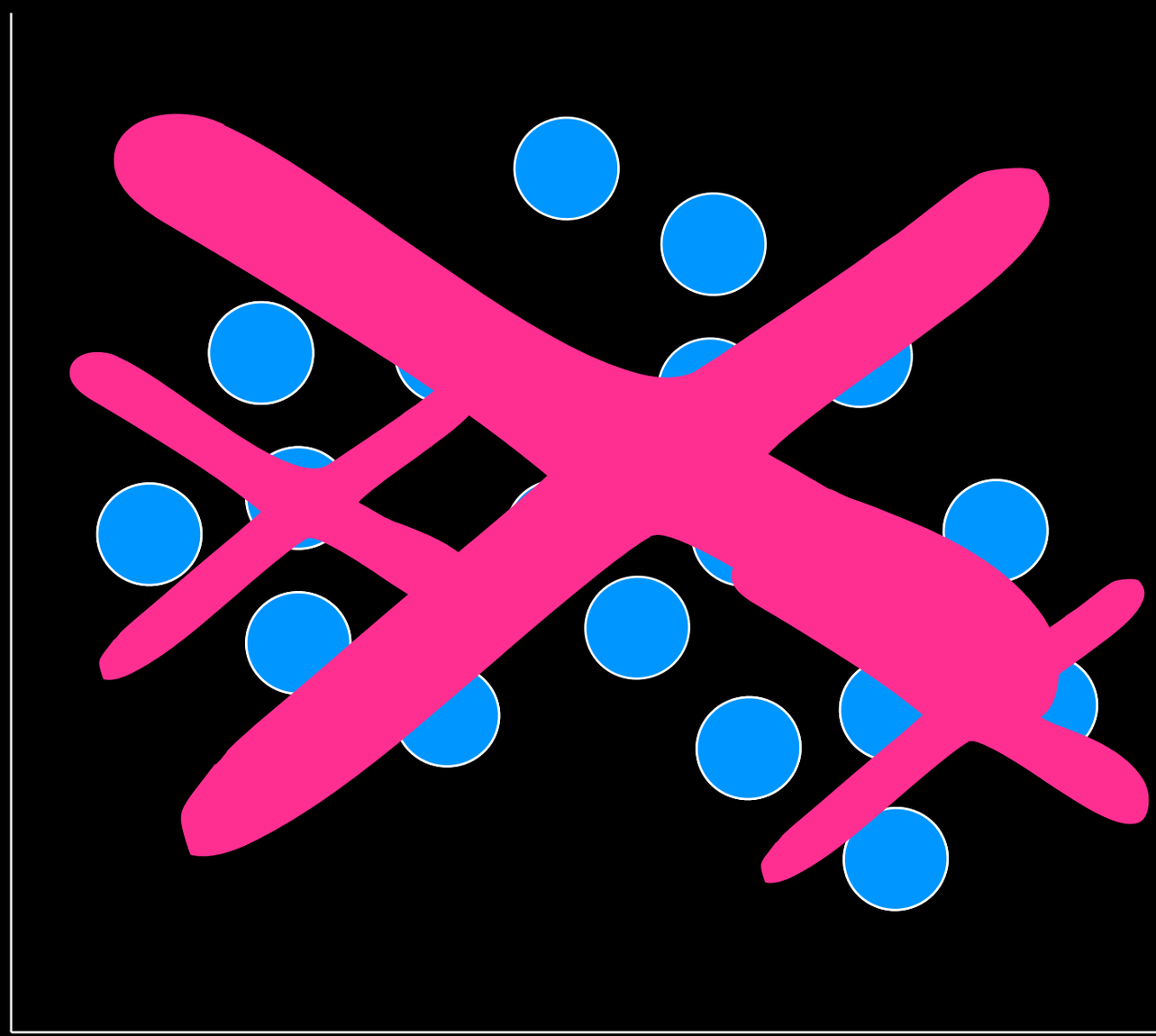
Don't Choose Subsets



"Young, left-handed, vegetarian atheists are significantly less likely to get X"

…but the population as a whole isn't!

Regularization

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Regularization

$$y = X w^T + e$$

D-BY-1

VECTOR

w^T

$||w||$

Regularization Norms

L1 NORM

$$||W||_1 = \sum_{i=1}^{N} |w_i|$$

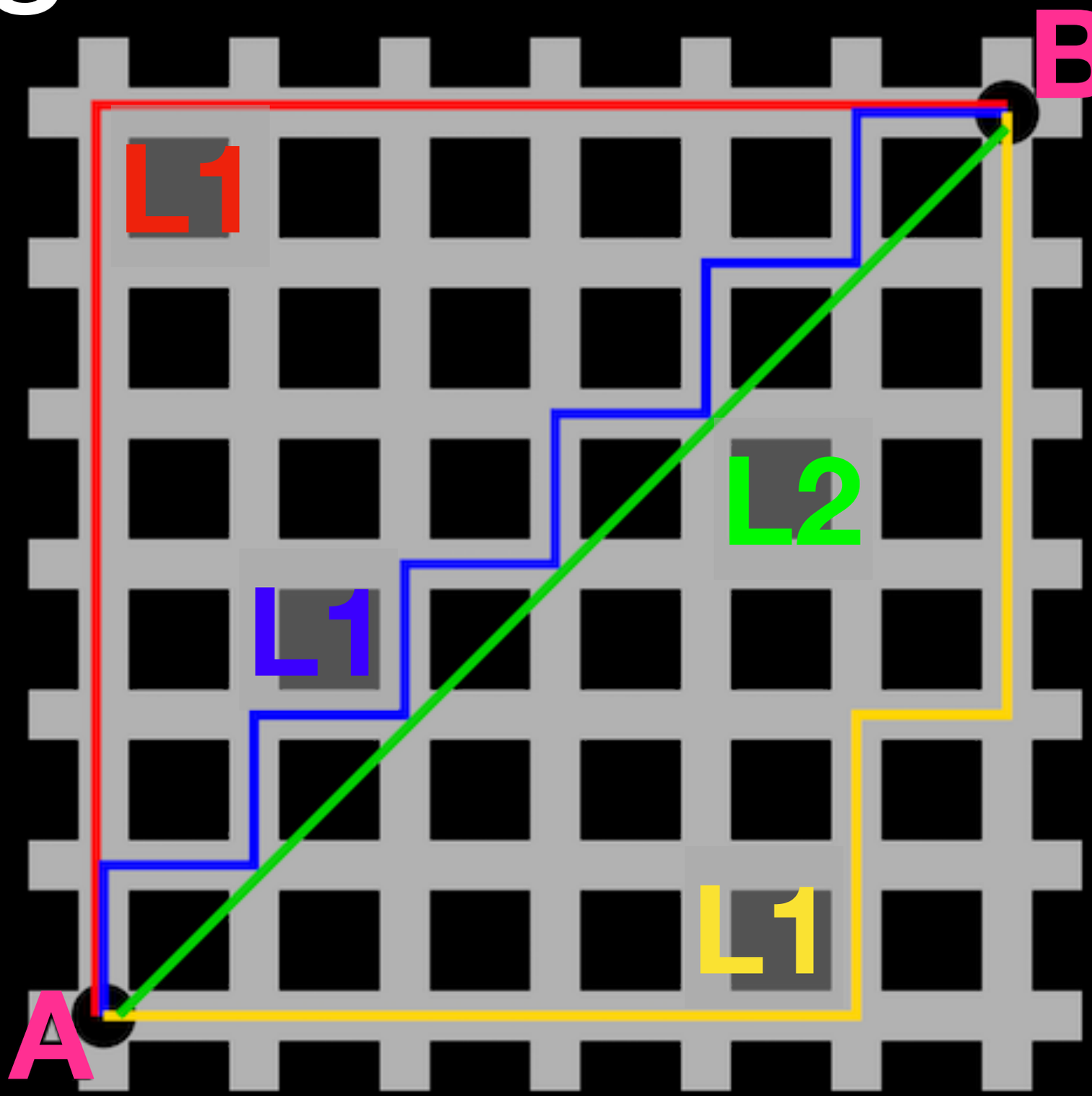
SPARSE

L2 NORM

$$||W||_2 = \sqrt{\sum_{i=1}^{N} w_i^2}$$

EVENLY DISTRIBUTED

Regularization Norms



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Feature Selection

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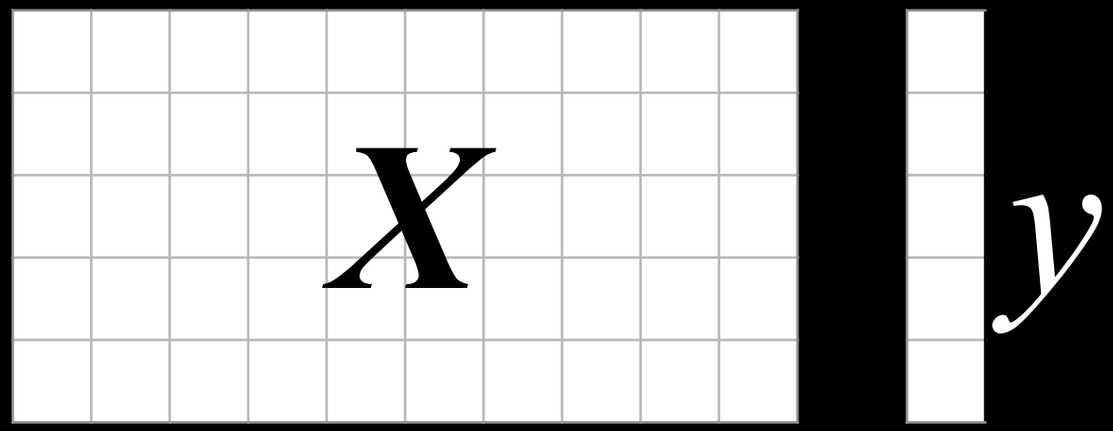
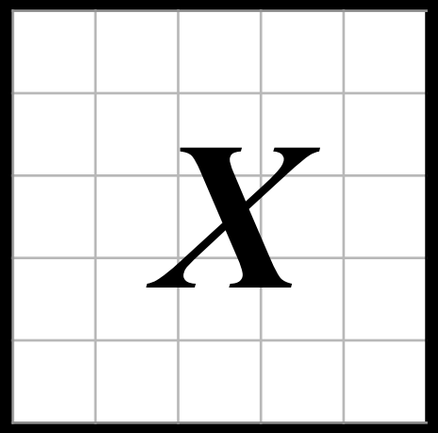
Dimensionality Reduction

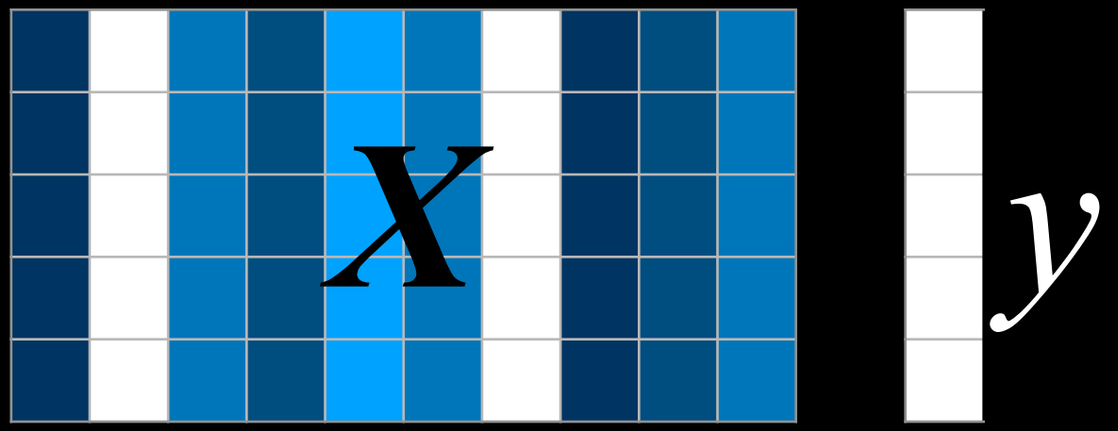


Reduce dimensionality to prevent spurious correlations with target

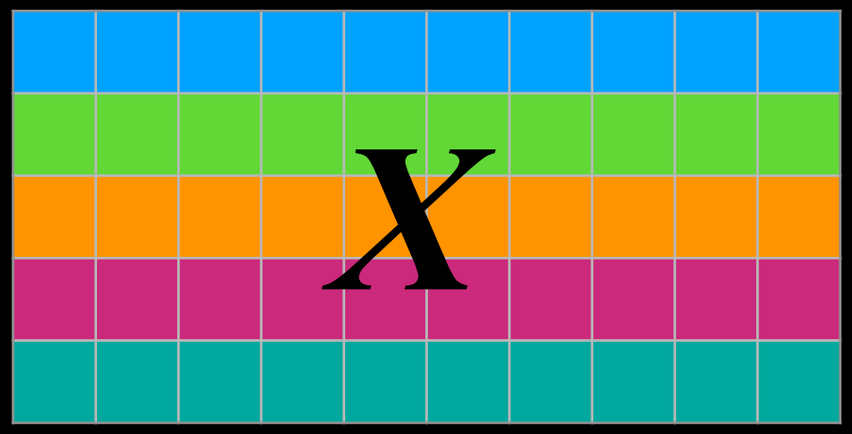


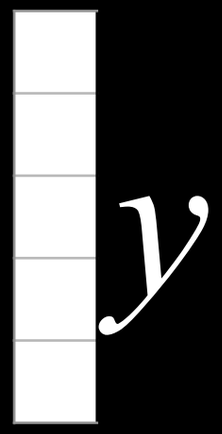
Chi-Squared

Measure Chi2 value (correlation) for each Feature with target



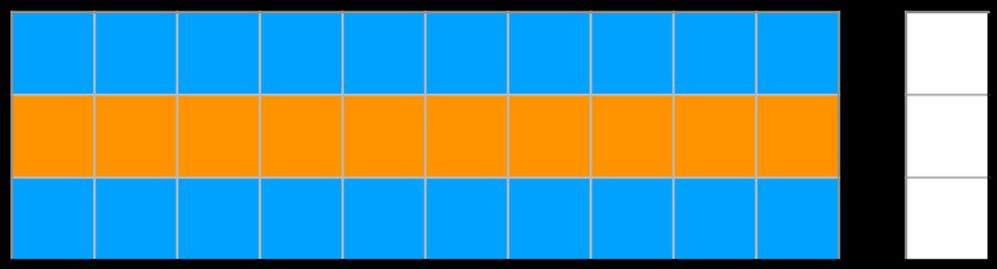
Randomized Logistic Regression





w^T

FIT N MODELS WI LI NORM ON SUBSETS



AVERAGE

Wrapping Up

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Take-home points

- Choose the **appropriate performance metric**
- Choose an **informative baseline**
- Measure **significance** of improvement
- **Regularize, regularize, regularize**
- **Feature selection** can improve performance and provide insights