Predictive Analysis: Evaluation and Experimentation

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October 2, 2013

Predictive Analysis

training

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	1	0	positive
0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

labeled examples

machine learning algorithm

model

testing

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	1	0	positive
0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

new, labeled examples

model

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_10	sentiment
1	0	1	0	1	0	0	1	1	0	positive
0	1	0	1	1	0	1	1	0	0	negative
0	1	0	1	1	0	1	0	0	0	negative
0	0	1	0	1	1	0	1	1	1	positive
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	0	1	1	0	0	1	0	1	positive

predictions

Evaluation

- Predictive analysis: training a model to make predictions on previously unseen data
- Evaluation: using previously unseen labeled data to estimate the quality of a model's predictions on new data
- Evaluation Metric: a measure that summarizes the quality of a model's predictions

Evaluation Metrics

- There are many different metrics
- Different metrics make different assumptions about what the “end users” cares about
- Choosing the most appropriate metric is important!

Evaluation Metrics
(1) accuracy

- Accuracy: percentage of correct predictions

true

		pos	neg
predicted	pos	a	b
	neg	c	d

$$\mathcal{A} = \frac{(a+d)}{(a+b+c+d)}$$

Evaluation Metrics
(1) accuracy

- Accuracy: percentage of correct predictions

true

predicted		pos	neut.	neg
	pos	a	b	c
	neut.	d	e	f
	neg	g	h	i

$$\mathcal{A} = \frac{(a+e+i)}{(a+b+c+d+e+f+g+h+i)}$$

Evaluation Metrics

(1) accuracy

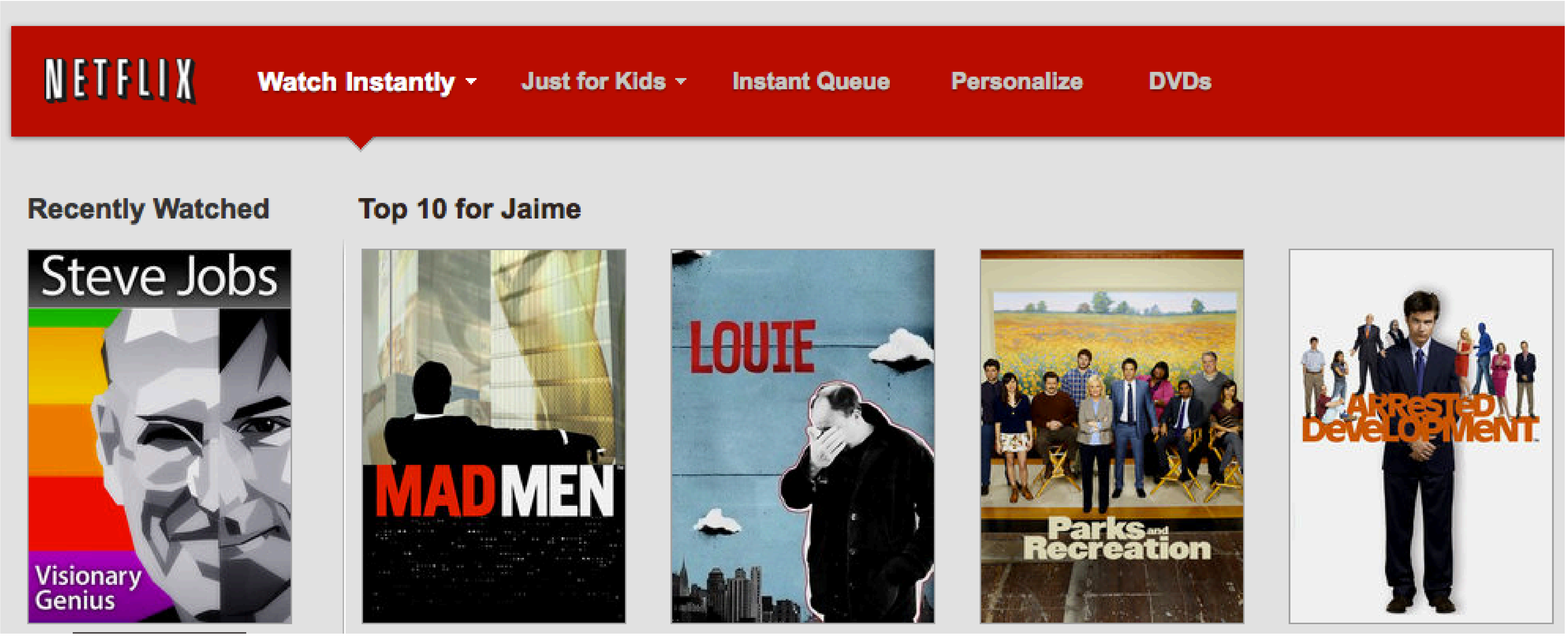
- What assumption(s) does accuracy make?

		true		
		pos	**neut.**	**neg**
predicted	**pos**	a	b	c
	neut.	d	e	f
	neg	g	h	i

$$\mathcal{A} = \frac{(a+e+i)}{(a+b+c+d+e+f+g+h+i)}$$

Evaluation Metrics

- Content recommendation: relevant vs. non-relevant



Evaluation Metrics

- Email spam filtering: spam vs. ham

From	Subject	Date Received	Categories
SUNDAY			
audio@DesktopTrainingOnline.com	Adobe Acrobat Pro: Instructor-Led Training t...	Sun 9/30/12 5:19 PM	Junk
THURSDAY			
ei-sci@ei-sci.org	SCI-EI期刊检索、收录 （ICIEEE 2013）邀请函	Thu 9/27/12 2:50 AM	Junk
WEDNESDAY			
The New York Times	Act now to receive FREE digital access PLUS 5...	Wed 9/26/12 3:49 PM	Junk
Citrix Systems	Give people the freedom to work anyplace	Wed 9/26/12 1:20 PM	Junk
LAST WEEK			
audio@DesktopTrainingOnline.com	Excel 2007/2010 Formatting & Customizing...	Mon 9/24/12 8:24 PM	Junk
Vonage	Last Chance: Unlimited calls with Vonage Basi...	Mon 9/24/12 2:56 PM	Junk
conference EDM	World's Tallest Tower in Tokyo – Join 2013 E...	Thu 9/20/12 10:48 PM	Junk
2 WEEKS AGO			
Jim Davidson & Strategic Investment	Washington Insider Comes out of the Shadow...	Tue 9/18/12 12:02 PM	Junk
audio@supertrainme.com	Student Record Retention: Secure Data, Maint...	Tue 9/18/12 6:56 AM	Junk
audio@DesktopTrainingOnline.com	Mastering Excel 2007/2010 Charts: Tips & Tri...	Thu 9/13/12 8:31 PM	Junk
3 WEEKS AGO			
Vonage	Get Unlimited Calling with Vonage Basic Talk...	Fri 9/7/12 2:41 PM	Junk
prof_qian	[EI SCOPUS ISI Journal, Beijing, China]Internati...	Fri 9/7/12 1:32 PM	Junk

Evaluation Metrics

- Product reviews: positive vs. negative vs. neutral

Evaluation Metrics

- Text-based Forecasting: buy vs. sell vs. hold

Evaluation Metrics

- Health monitoring system: alarm vs. no alarm

Evaluation Metrics
(1) accuracy

- What assumption(s) does accuracy make?
- It assumes that all prediction errors are equally bad
- Oftentimes, we care more about one class than the others
- If so, the class of interest is usually the minority class
- We are looking for the “needles in the haystack”
- In this case, accuracy is not a good evaluation metric
- There are metrics that provide more insight into per-class performance

Evaluation Metrics

(2) precision and (3) recall

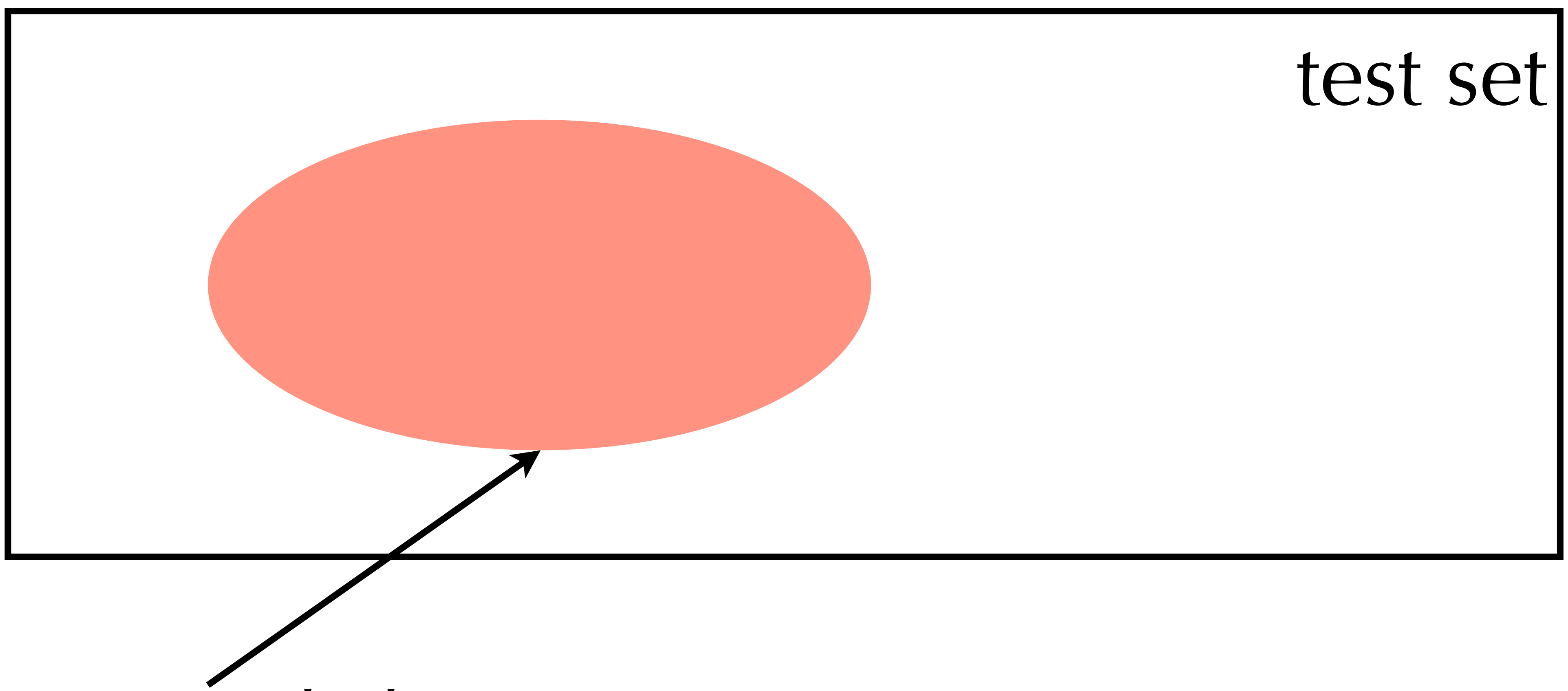
- For a given class **C**:
  - precision: the percentage of positive predictions that are truly positive
  - recall: the percentage of true positives that are correctly predicted positive

Evaluation Metrics

(2) precision and (3) recall

test set

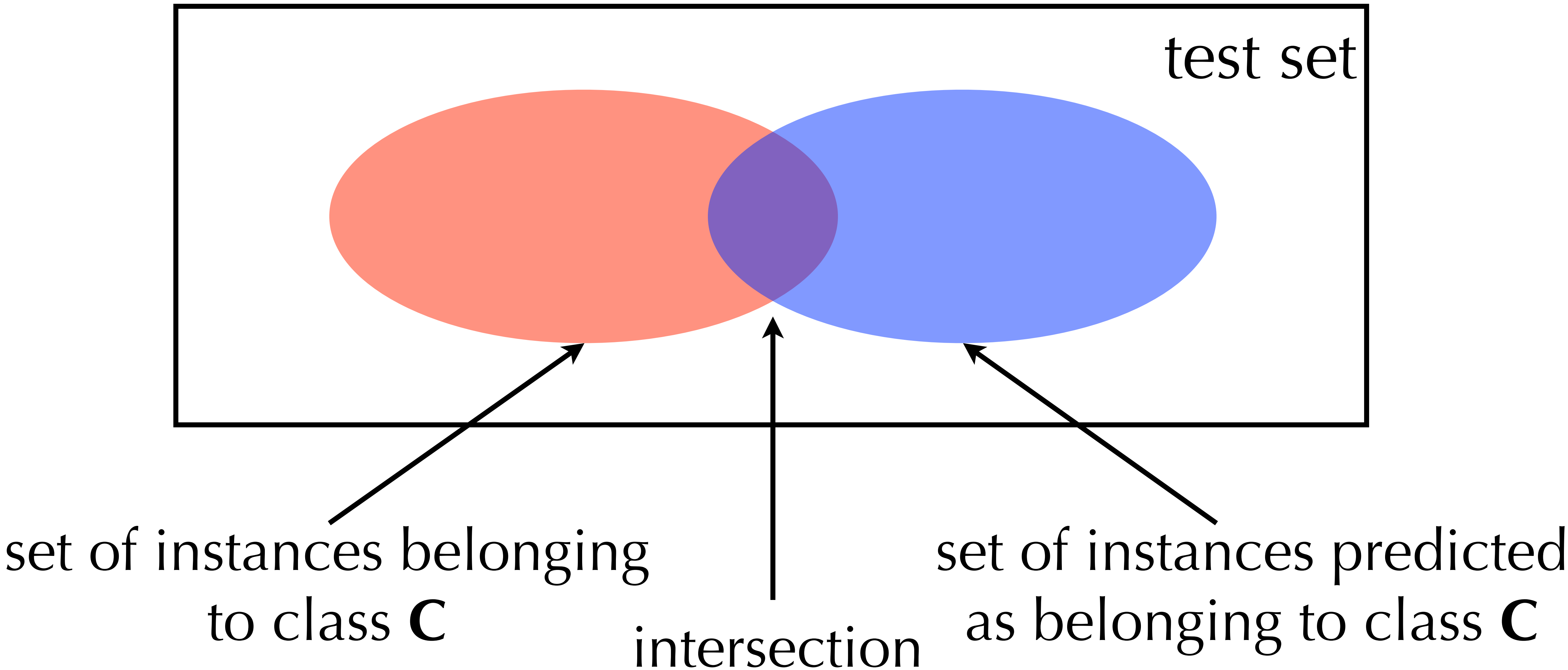
Evaluation Metrics
(2) precision and (3) recall



set of instances belonging
to class **C**

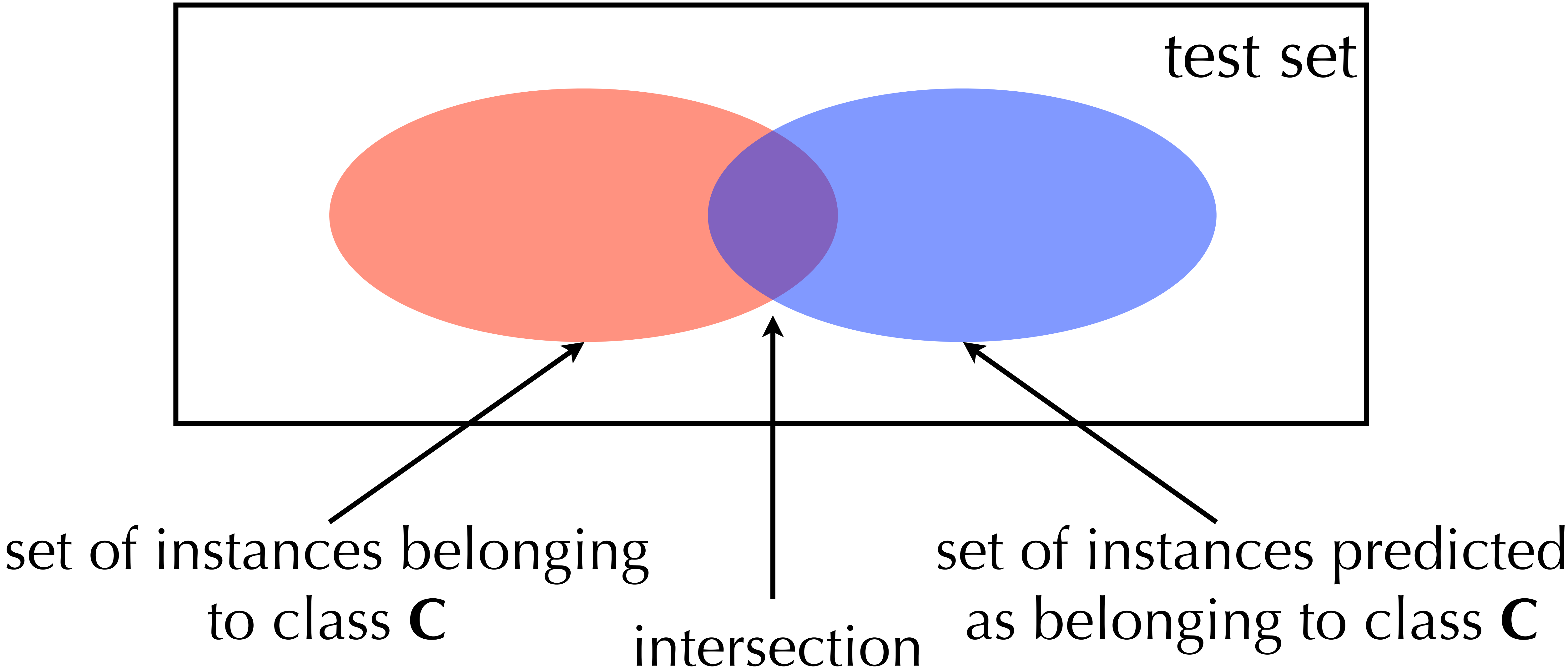
Evaluation Metrics

(2) precision and (3) recall



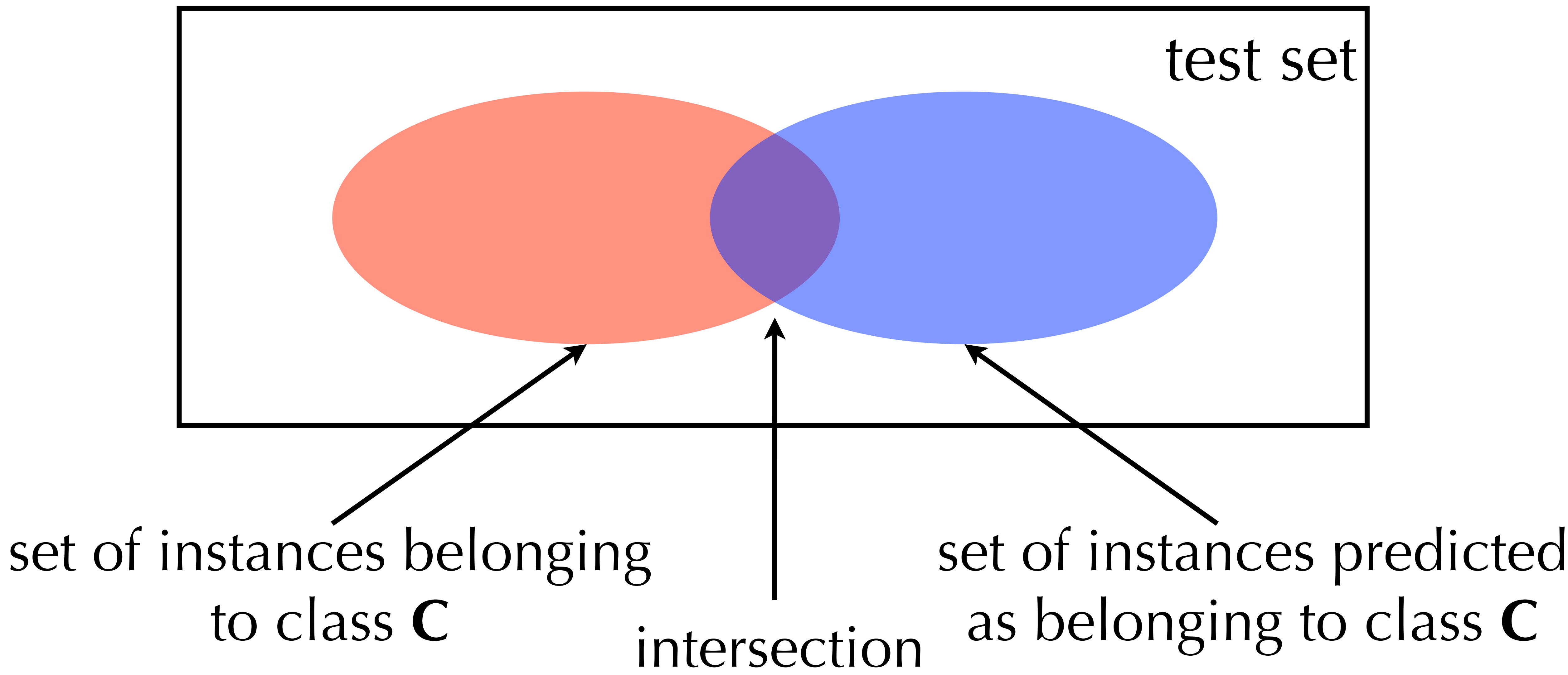
Evaluation Metrics
(2) precision and (3) recall

- Precision = ?



Evaluation Metrics
(2) precision and (3) recall

- Recall = ?



Evaluation Metrics

(2) precision and (3) recall

true

predicted

	pos	neut.	neg
pos	a	b	c
neut.	d	e	f
neg	g	h	i

$$\mathcal{P}_{\text{positive}} = \frac{a}{a+b+c}$$

Evaluation Metrics

(2) precision and (3) recall

		true		
		pos	neut.	neg
predicted	pos	a	b	c
	neut.	d	e	f
	neg	g	h	i

$$\mathcal{R}_{\text{positive}} = \frac{a}{a+d+g}$$

Evaluation Metrics

(2) precision and (3) recall

		true		
		pos	neut.	neg
predicted	pos	a	b	c
	neut.	d	e	f
	neg	g	h	i

$$\mathcal{P}_{\text{neutral}} = ?$$

Evaluation Metrics
(2) precision and (3) recall

		true		
		pos	neut.	neg
predicted	pos	a	b	c
	neut.	d	e	f
	neg	g	h	i

$$\mathcal{P}_{\text{neutral}} = \frac{e}{d + e + f}$$

Evaluation Metrics

(2) precision and (3) recall

predicted (rows) / **true** (columns)

	pos	neut.	neg
pos	a	b	c
neut.	d	e	f
neg	g	h	i

$$\mathcal{R}_{\text{neutral}} = ?$$

Evaluation Metrics
(2) precision and (3) recall

true (columns) / **predicted** (rows)

	pos	neut.	neg
pos	a	b	c
neut.	d	e	f
neg	g	h	i

$$\mathcal{R}_{\text{neutral}} = \frac{e}{b+e+h}$$

Evaluation Metrics

(2) precision and (3) recall

		true		
		pos	neut.	neg
predicted	pos	a	b	c
	neut.	d	e	f
	neg	g	h	i

$$\mathcal{P}_{\text{negative}} = \frac{i}{g+h+i}$$

Evaluation Metrics

(2) precision and (3) recall

		true		
		pos	neut.	neg
predicted	pos	a	b	c
	neut.	d	e	f
	neg	g	h	i

$$\mathcal{R}_{\text{negative}} = \frac{i}{c + f + i}$$

Evaluation Metrics

(2) precision and (3) recall

- Precision and recall provide complementary views
- In some cases, we want a balance of precision and recall
- How can we combine precision and recall to produce one measure of performance for a particular class?
- We could use the (arithmetic) mean of precision and recall
- Why would this be a bad idea?

$$\frac{\mathcal{P} + \mathcal{R}}{2}$$

Evaluation Metrics

(2) precision and (3) recall

- Precision and recall are easy to "game"
- Maximize precision: predict only the few most confident instances as belonging to class **C**
- Maximize recall: predict all instances as belonging to class **C**

Evaluation Metrics
(2) precision and (3) recall

- Based on the arithmetic mean:
  - perfect precision and abysmal recall ≈ 0.5
  - perfect recall and abysmal precision ≈ 0.5
  - medium precision and medium precision ≈ 0.5

$$\frac{\mathcal{P} + \mathcal{R}}{2}$$

Evaluation Metrics

(4) f-measure

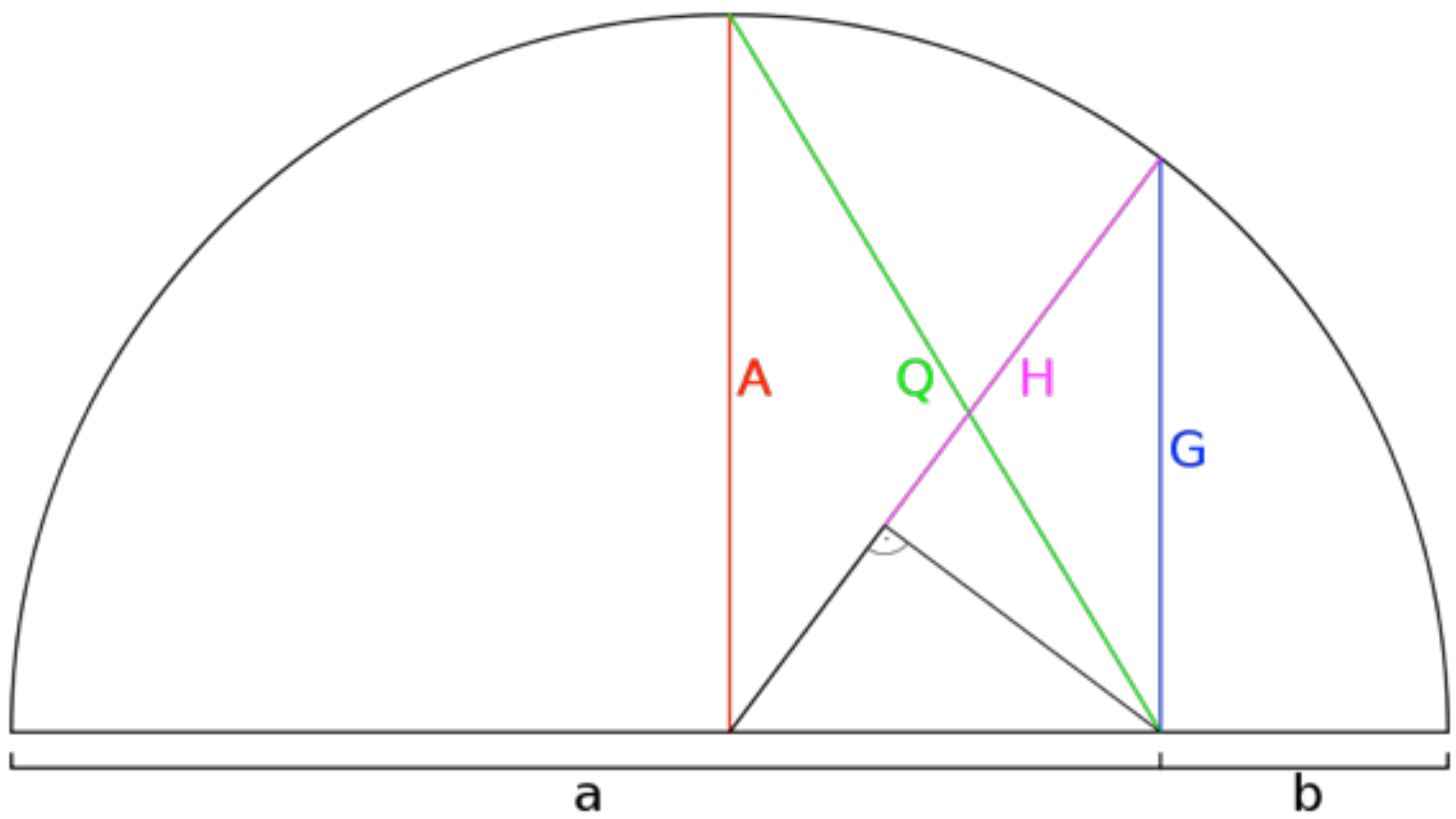
- F-measure: the harmonic (not arithmetic) mean of precision and recall

$$\mathcal{F} = \frac{2 \times \mathcal{P} \times \mathcal{R}}{\mathcal{P} + \mathcal{R}}$$

Evaluation Metrics

(4) f-measure

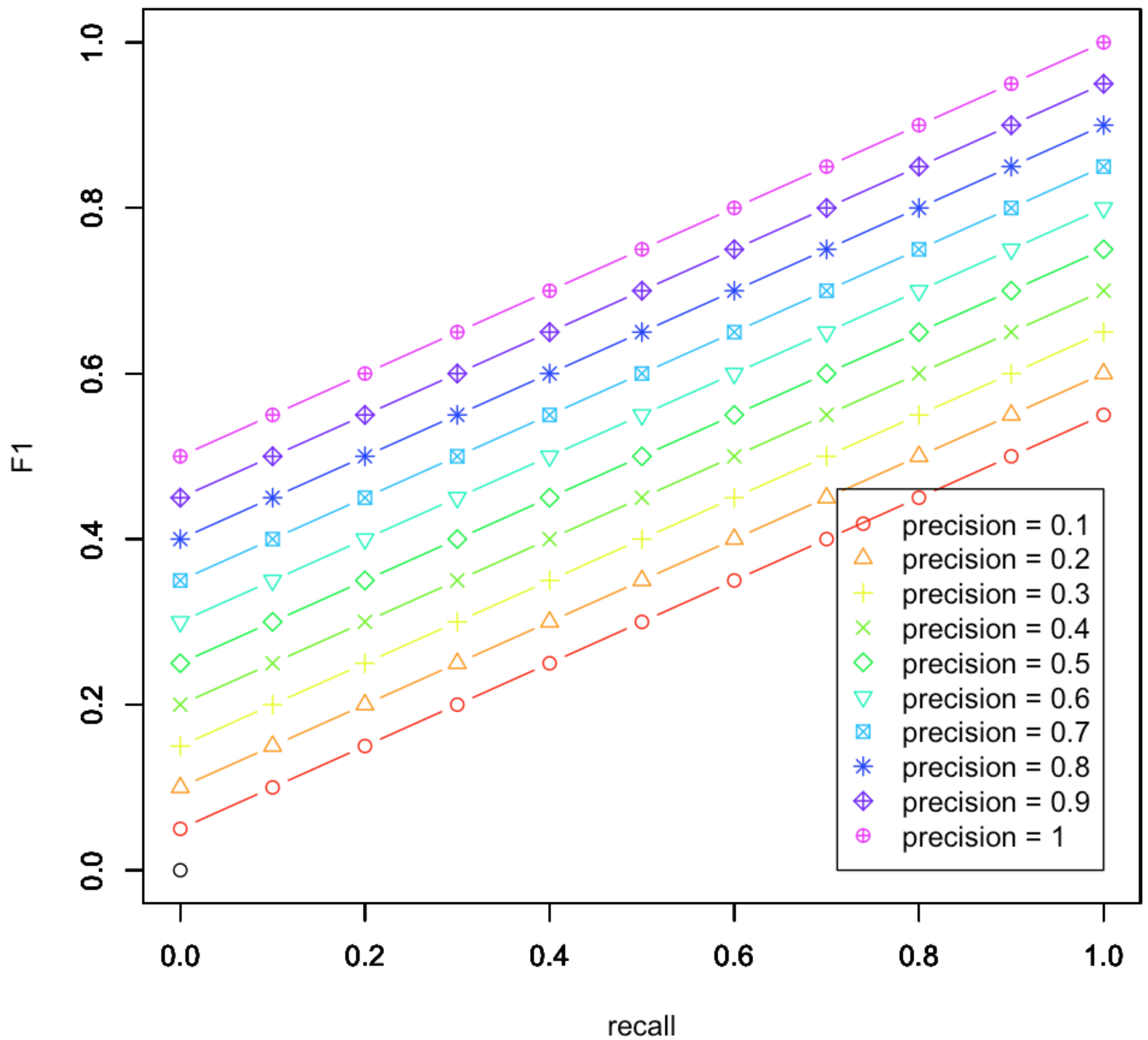
- F-measure: the harmonic (not arithmetic) mean of precision and recall

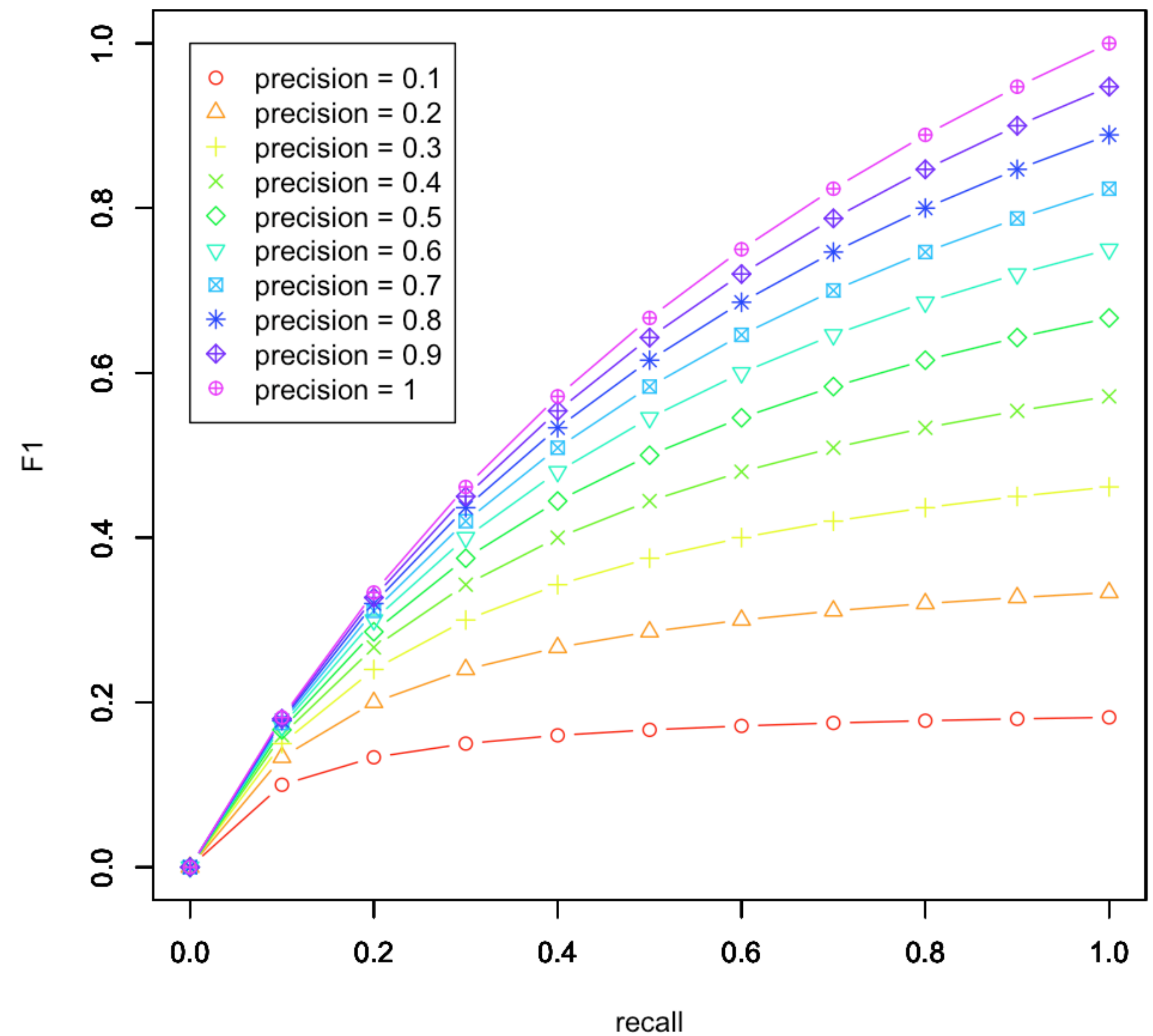


source: http://en.wikipedia.org/wiki/Harmonic_mean

Evaluation Metrics
(4) f-measure

- F-measure: the harmonic (not arithmetic) mean of precision and recall





(slide courtesy of Ben Carterette)

Evaluation Metrics
(5) precision-recall curves

- F-measure: assumes that the "end users" care <u>equally</u> about precision and recall

Evaluation Metrics

(5) precision-recall curves

- Most machine-learning algorithms provide a prediction confidence value
- The prediction confidence value can be used as a threshold in order to trade-off precision and recall

Evaluation Metrics
(5) precision-recall curves

- Remember Naive Bayes classification?
- Given instance D, predict positive (POS) if:

$$P(POS|D) \geq P(NEG|D)$$

- Otherwise, predict negative (NEG)

Evaluation Metrics

(5) precision-recall curves

- Remember Naive Bayes classification?
- Given instance D, predict positive (POS) if:

$$\boxed{P(POS|D)} \geq P(NEG|D)$$

- Otherwise, predict negative (NEG)

this value can be used as a threshold for classification into the POS class

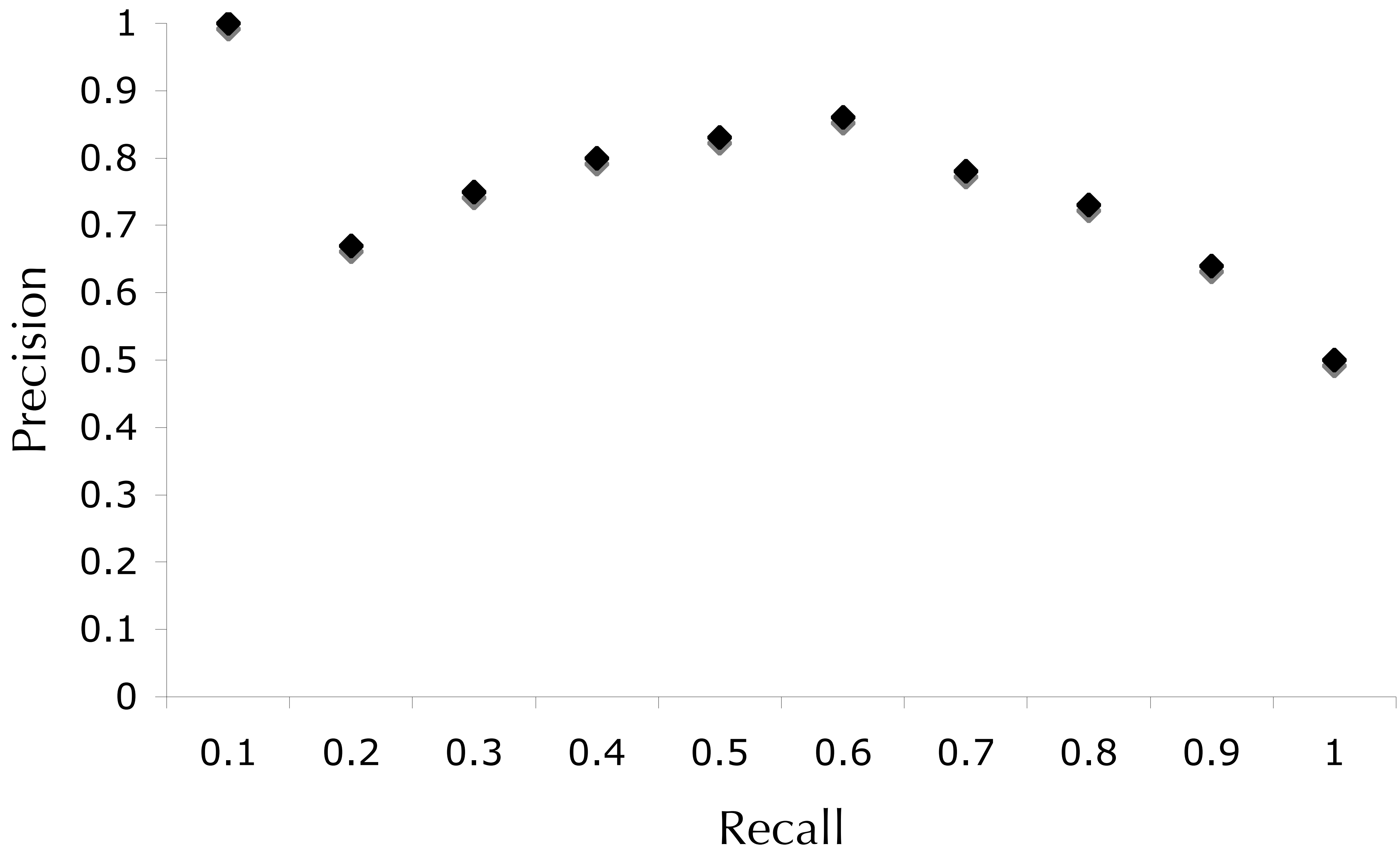
Evaluation Metrics

(5) precision-recall curves

rank (K)	ranking	P(POS|D)	P@K	R@K
1		0.99	1.00	0.10
2		0.87	0.50	0.10
3		0.84	0.67	0.20
4		0.83	0.75	0.30
5		0.77	0.80	0.40
6		0.63	0.83	0.50
7		0.58	0.86	0.60
8		0.57	0.75	0.60
9		0.56	0.78	0.70
10		0.34	0.70	0.70
11		0.33	0.73	0.80
12		0.25	0.67	0.80
13		0.21	0.62	0.80
14		0.15	0.64	0.90
15		0.14	0.60	0.90
16		0.14	0.56	0.90
17		0.12	0.53	0.90
18		0.08	0.50	0.90
19		0.01	0.47	0.90
20		0.01	0.50	1.00

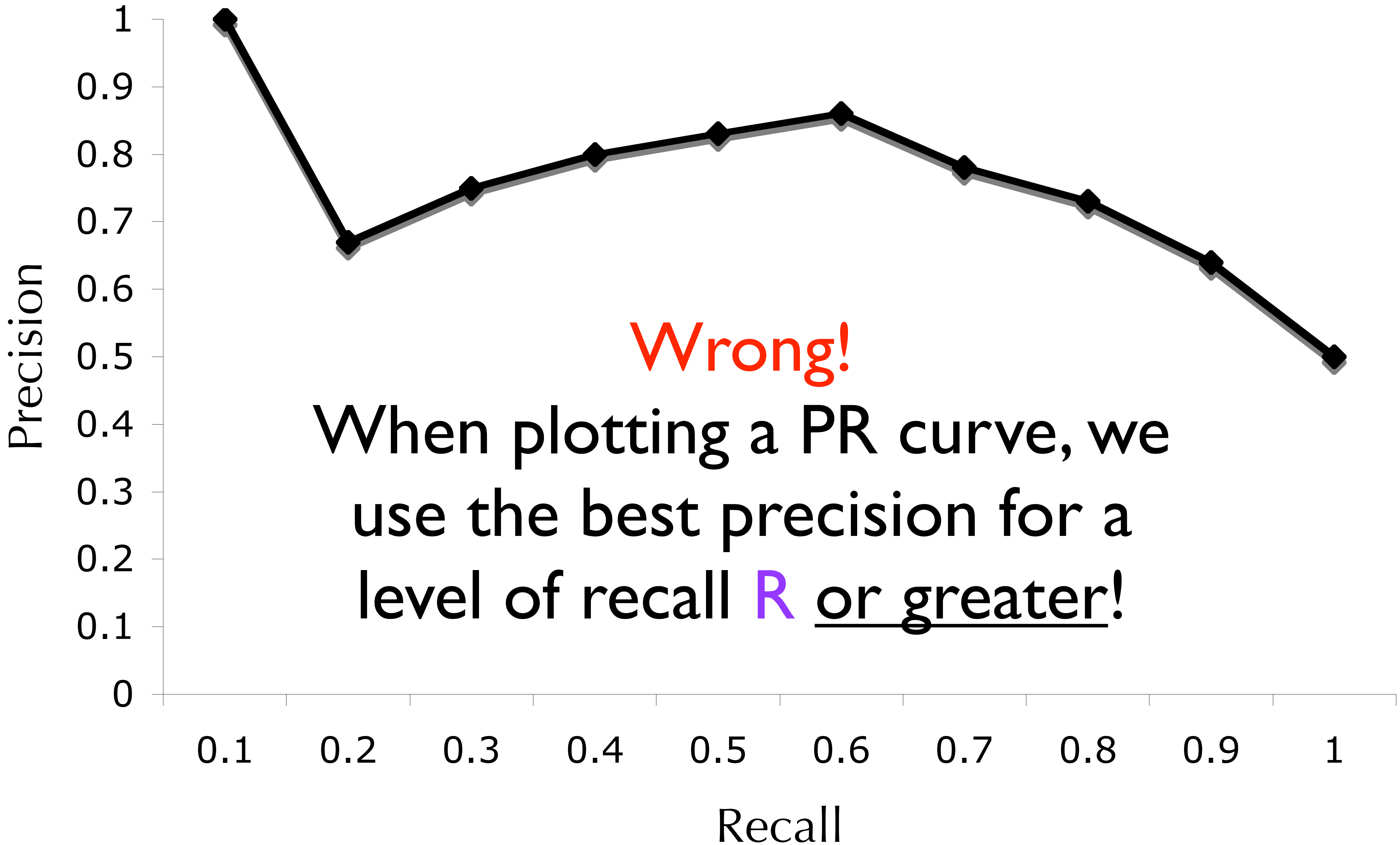
Evaluation Metrics

(5) precision-recall curves

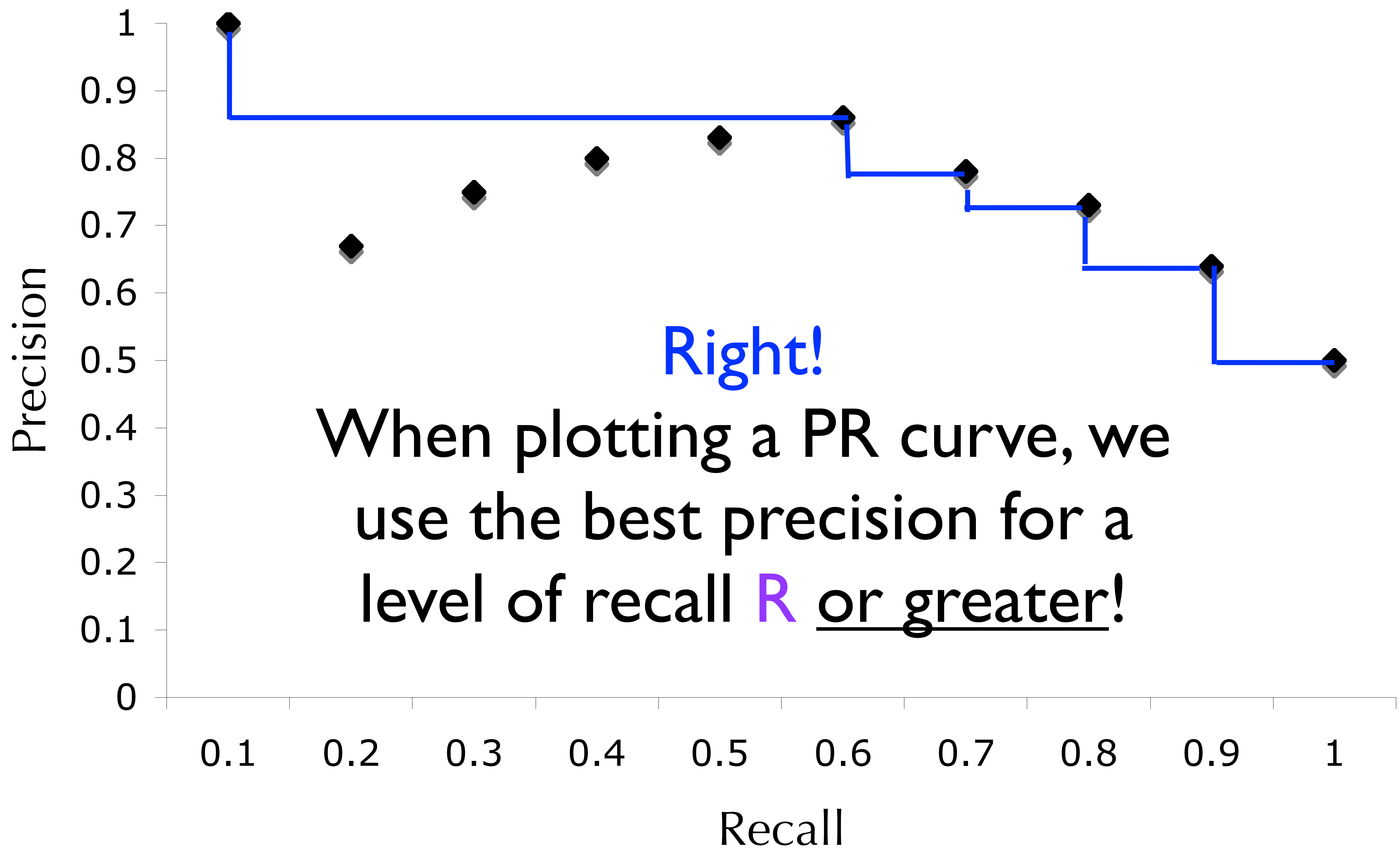


Evaluation Metrics

(5) precision-recall curves



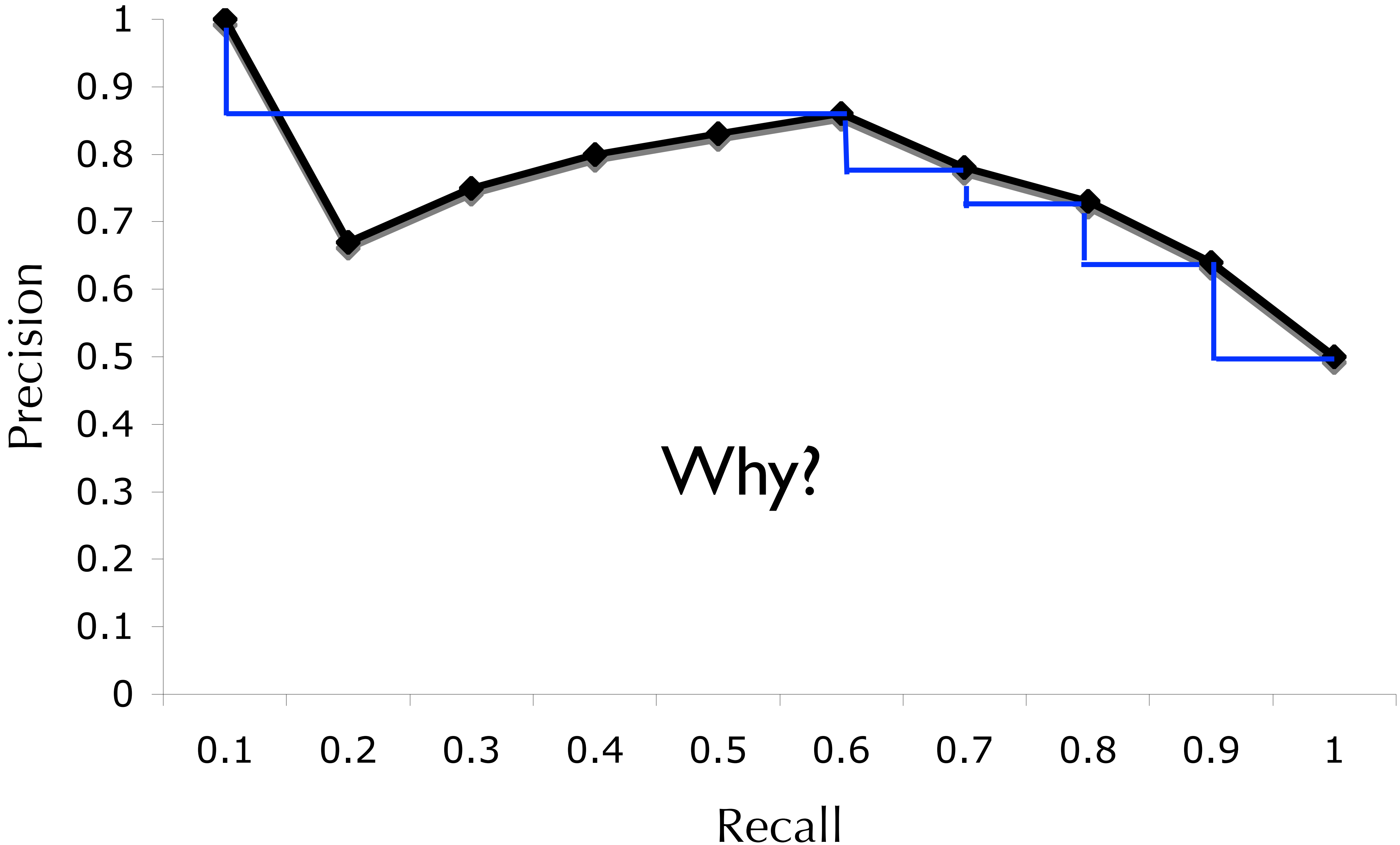
Evaluation Metrics
(5) precision-recall curves



Right!

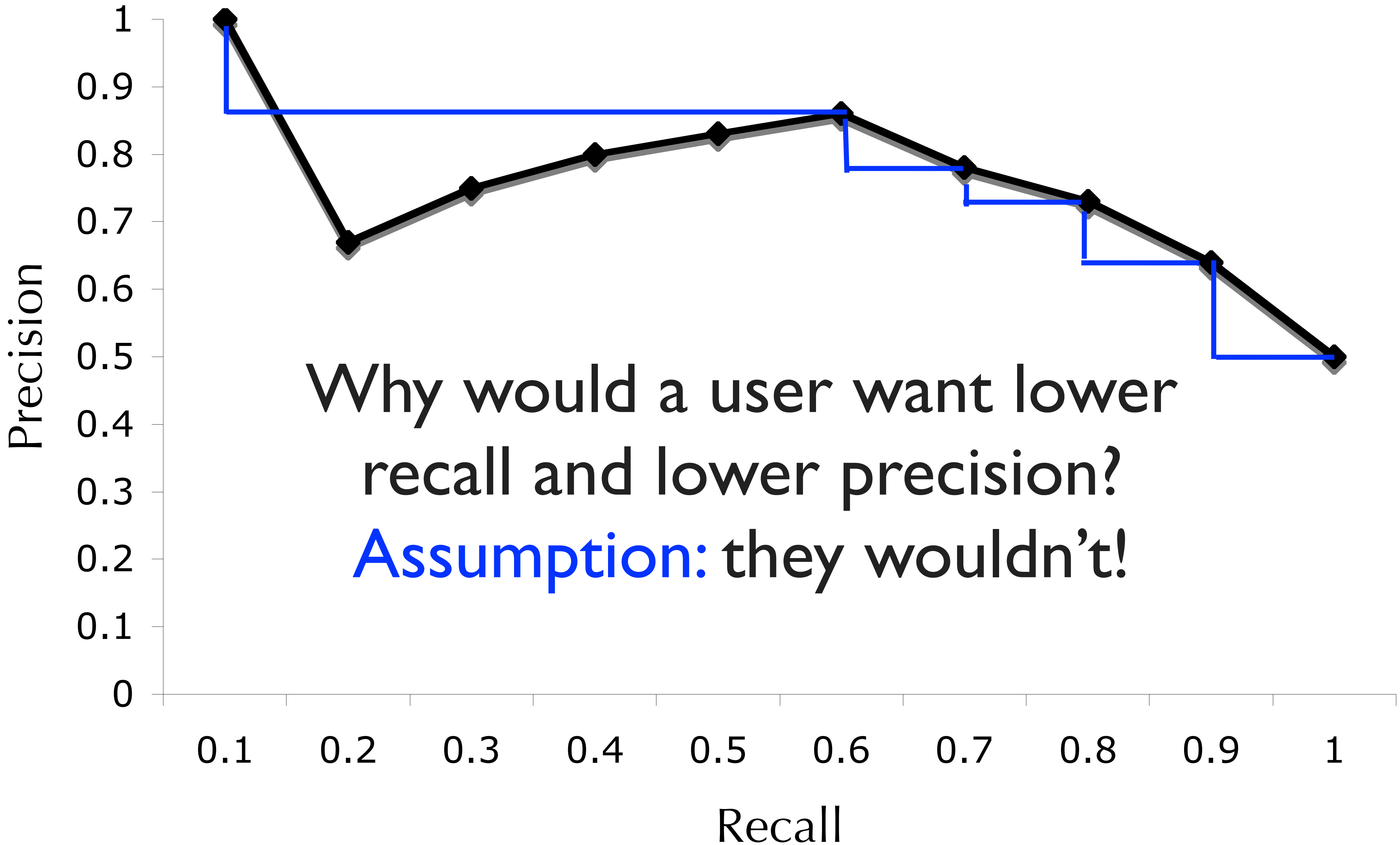
When plotting a PR curve, we use the best precision for a level of recall R <u>or greater</u>!

Evaluation Metrics
(5) precision-recall curves

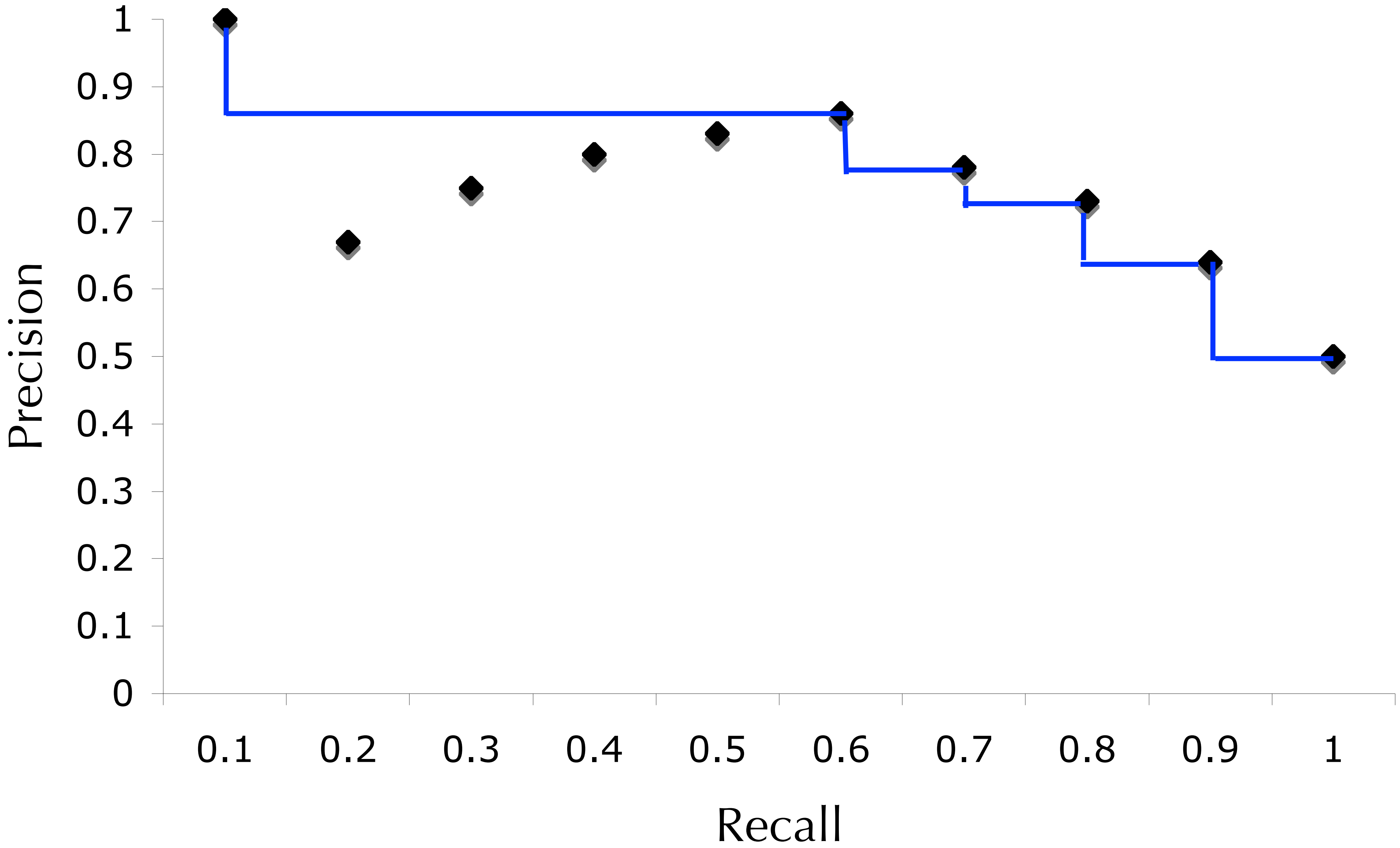


Evaluation Metrics

(5) precision-recall curves

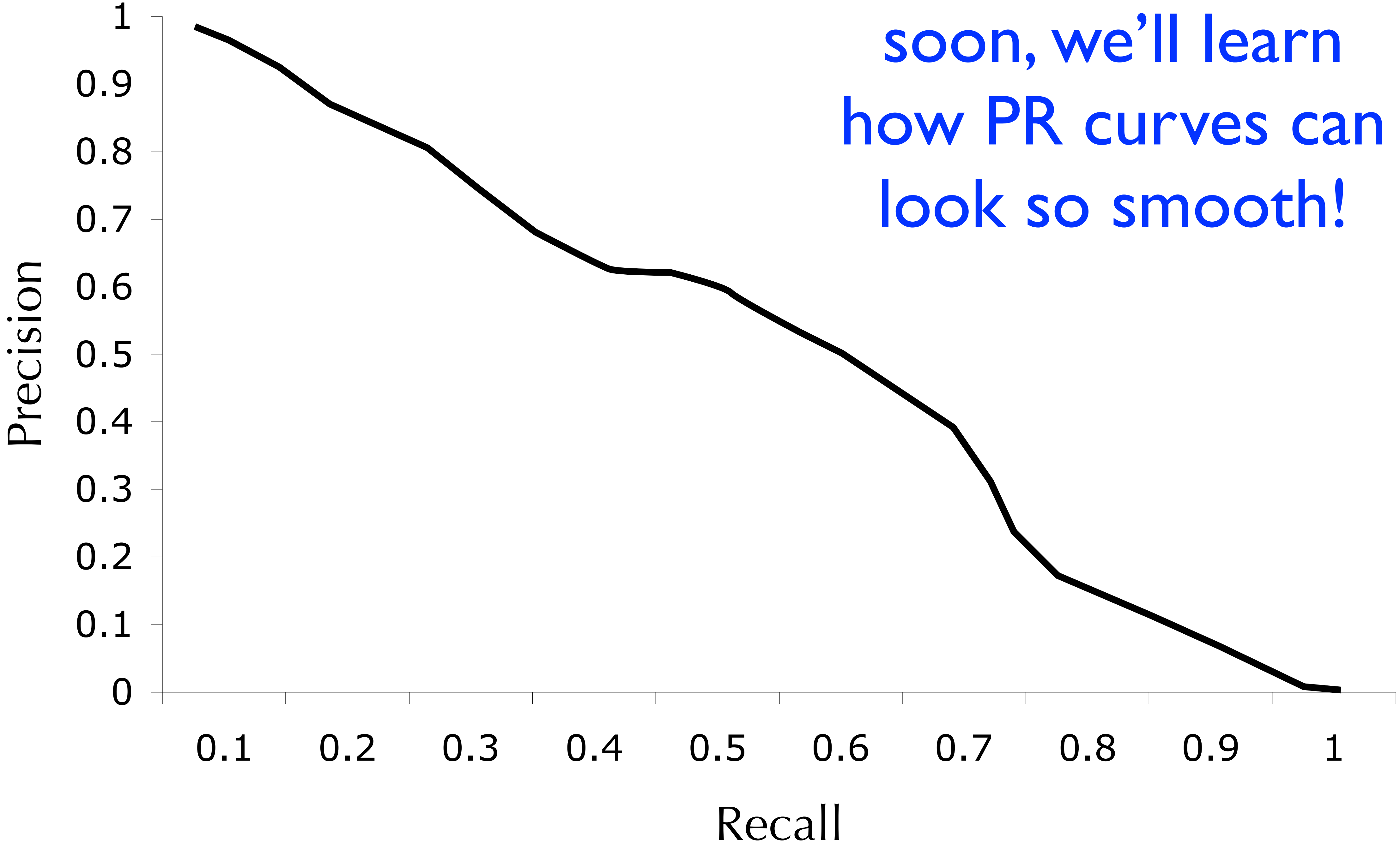


Evaluation Metrics
(5) precision-recall curves



Evaluation Metrics

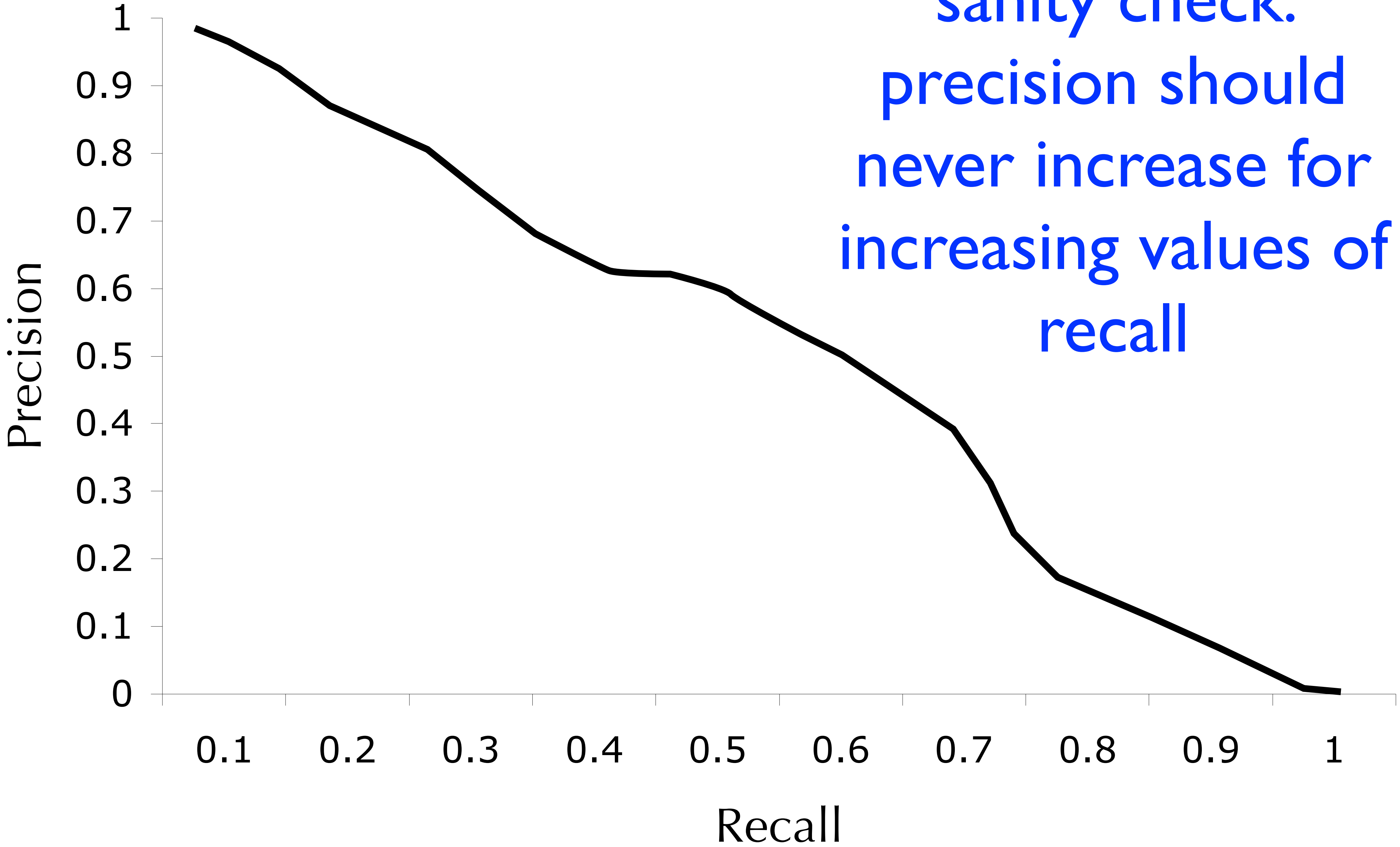
(5) precision-recall curves



soon, we'll learn how PR curves can look so smooth!

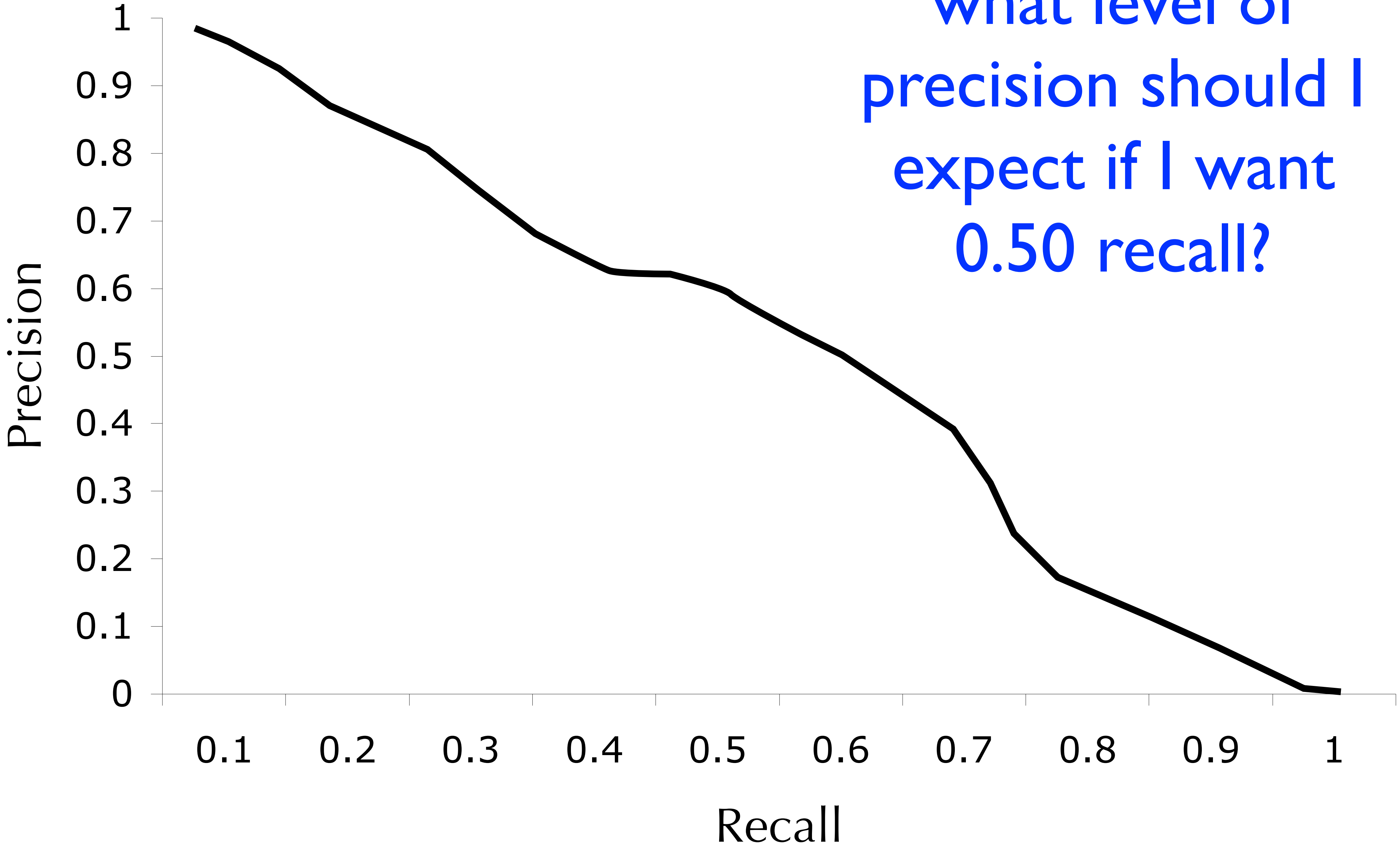
Evaluation Metrics

(5) precision-recall curves



sanity check: precision should never increase for increasing values of recall

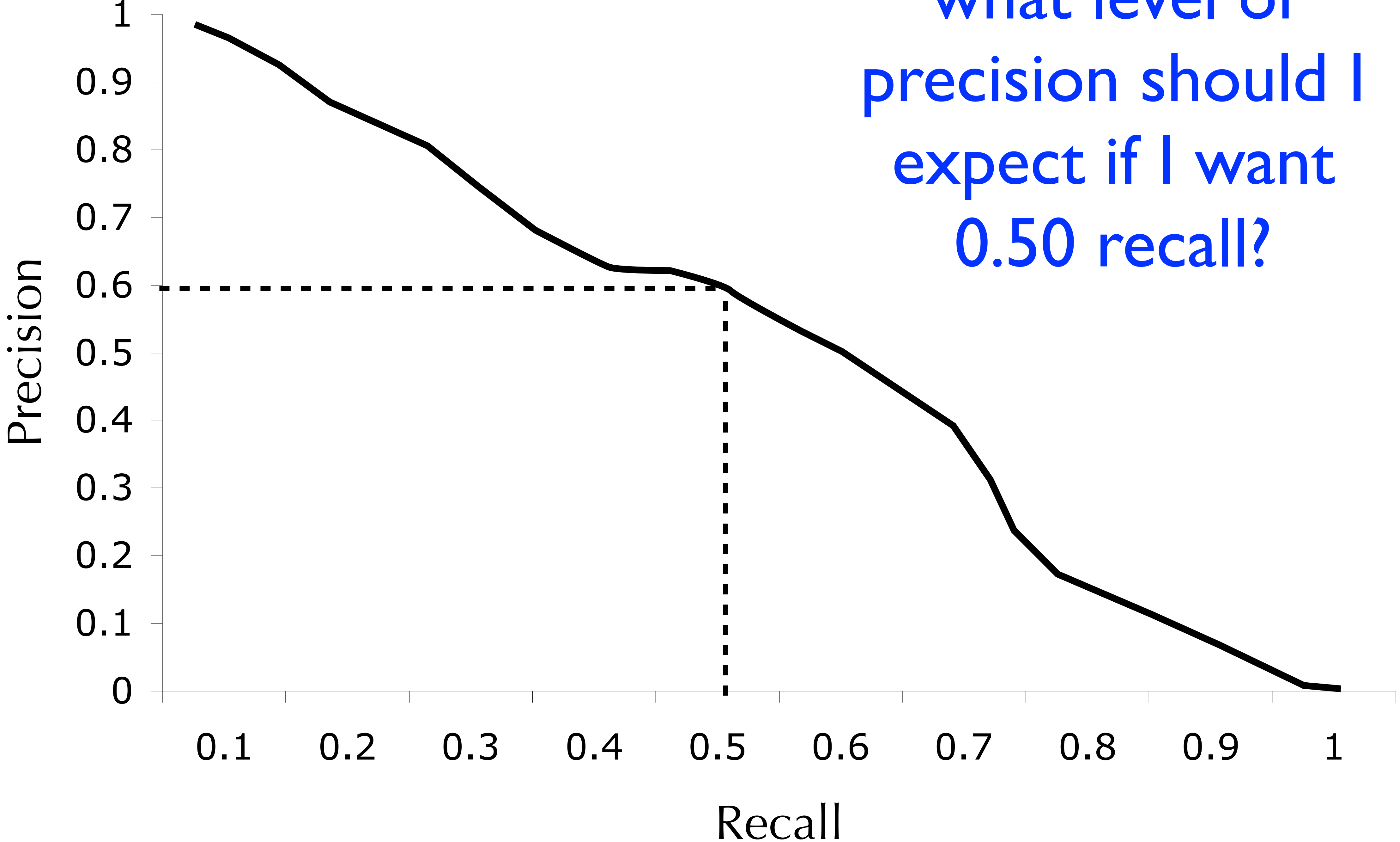
Evaluation Metrics
(5) precision-recall curves



what level of precision should I expect if I want 0.50 recall?

Evaluation Metrics

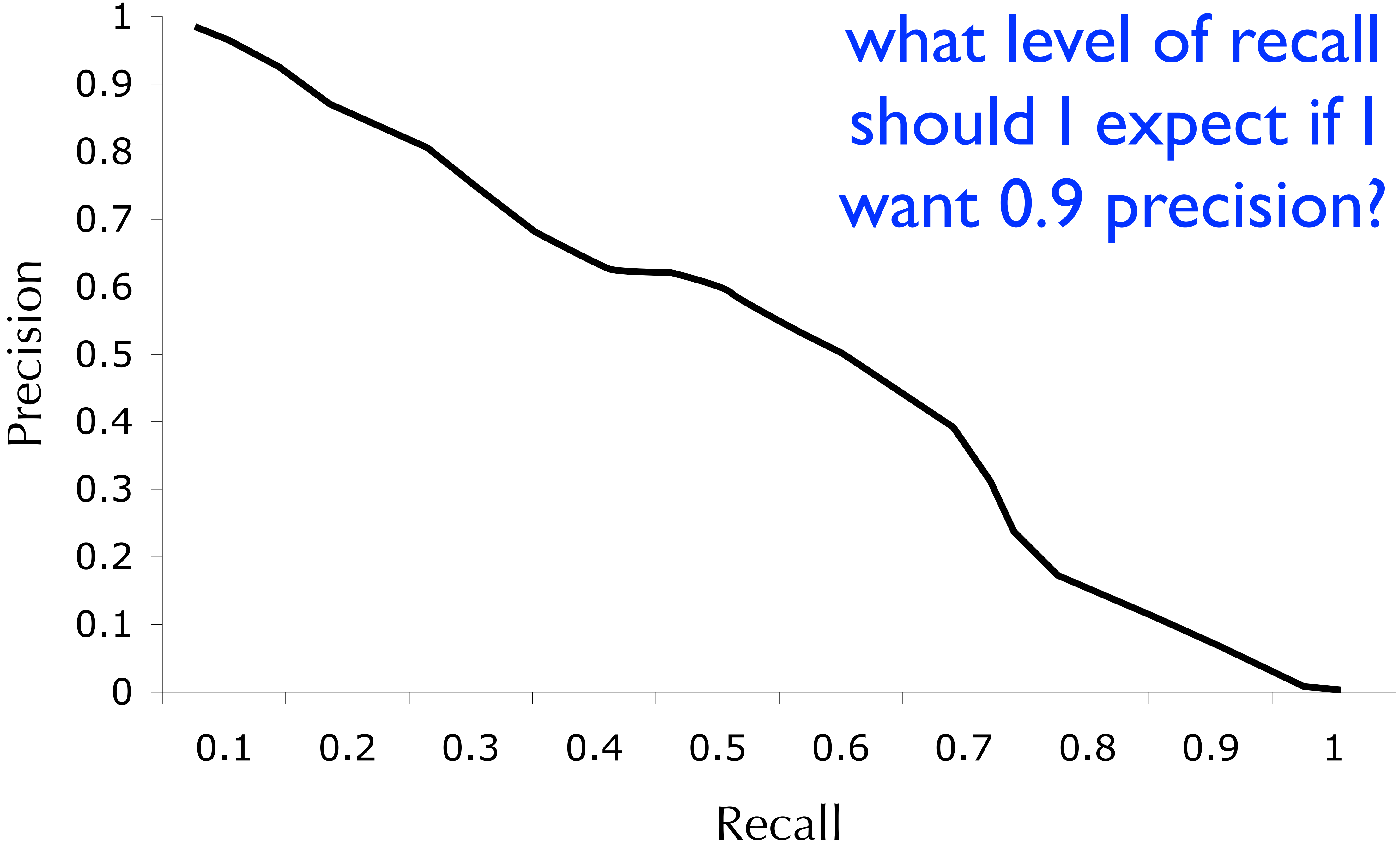
(5) precision-recall curves



what level of precision should I expect if I want 0.50 recall?

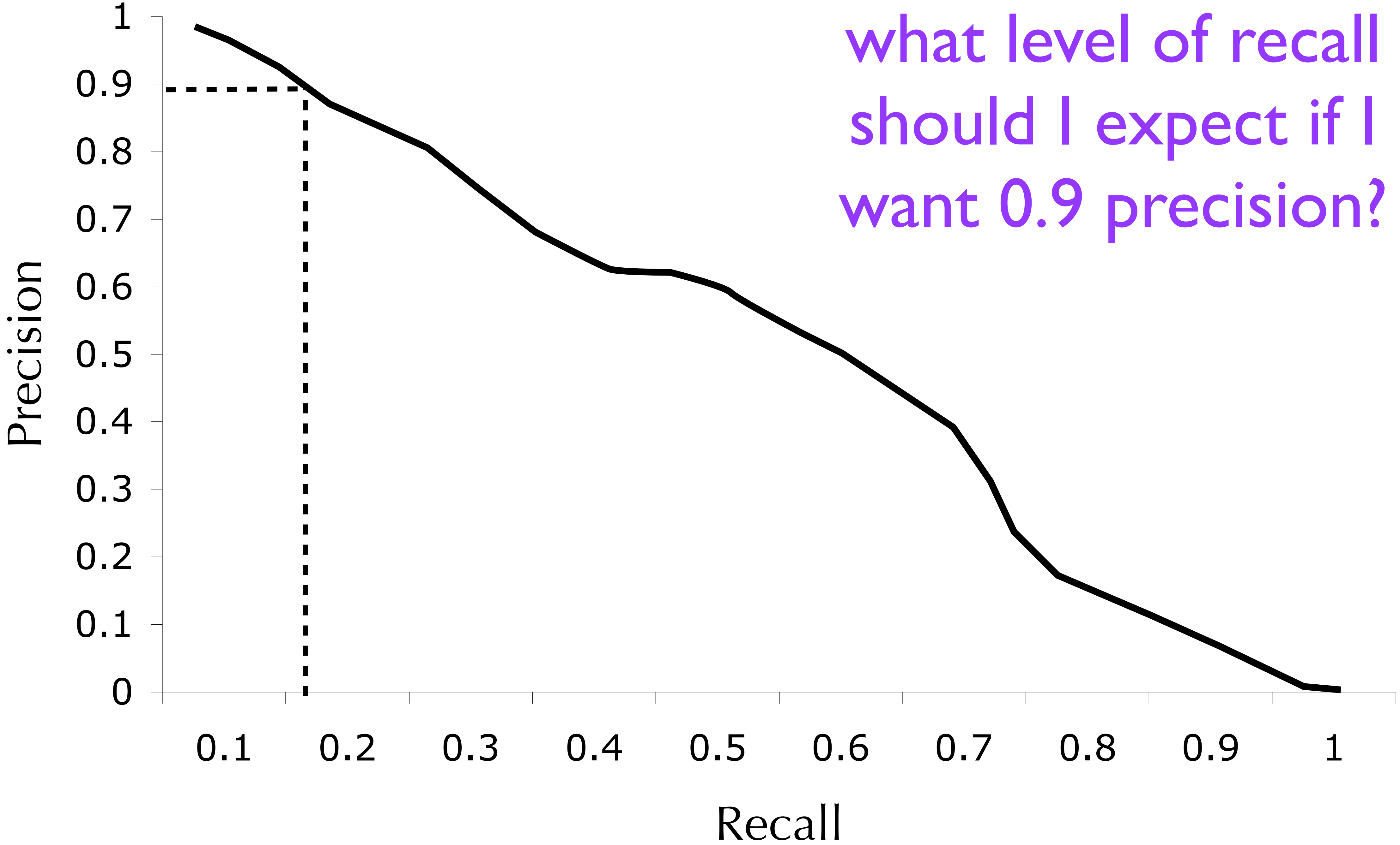
Evaluation Metrics

(5) precision-recall curves



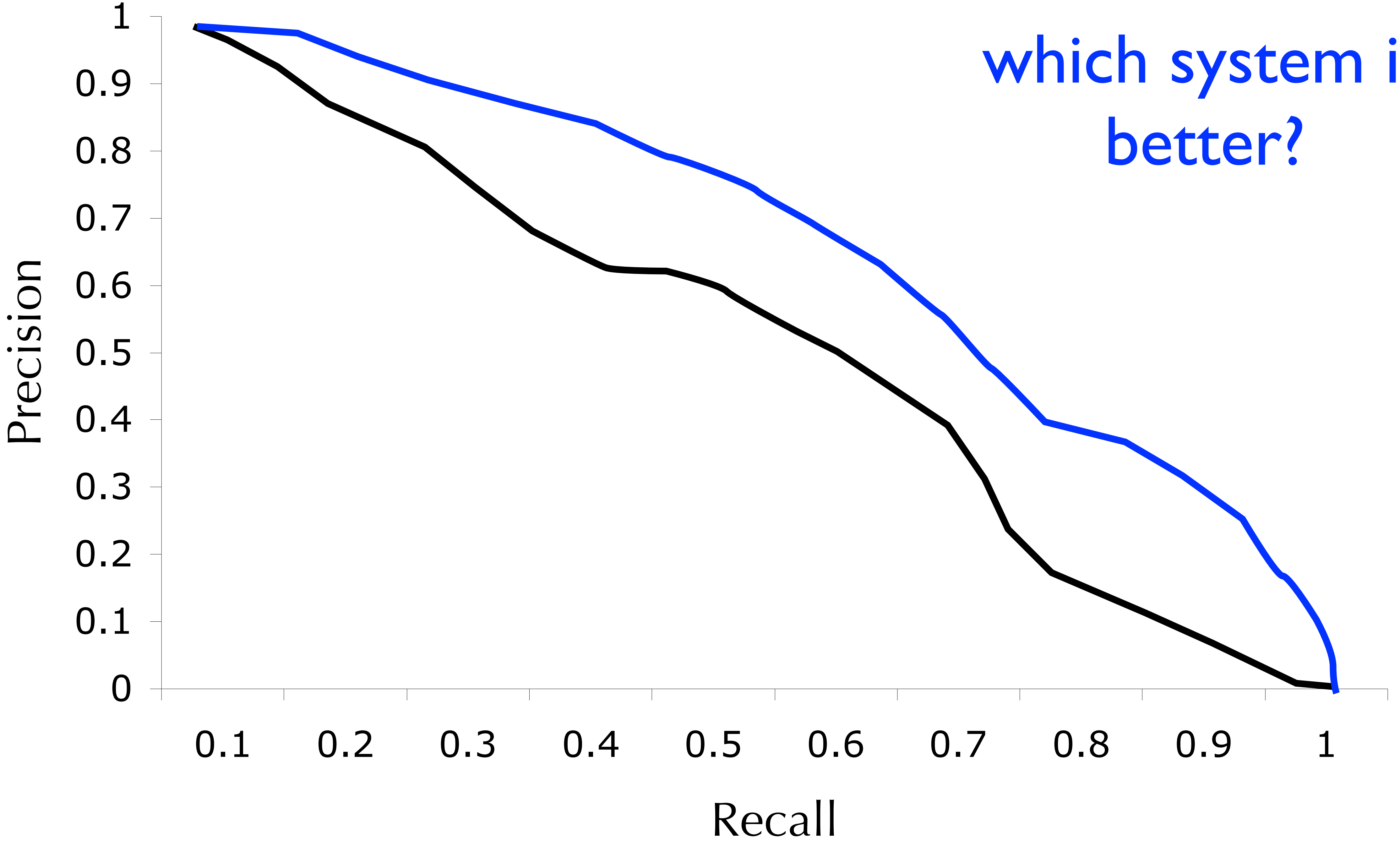
what level of recall should I expect if I want 0.9 precision?

Evaluation Metrics
(5) precision-recall curves



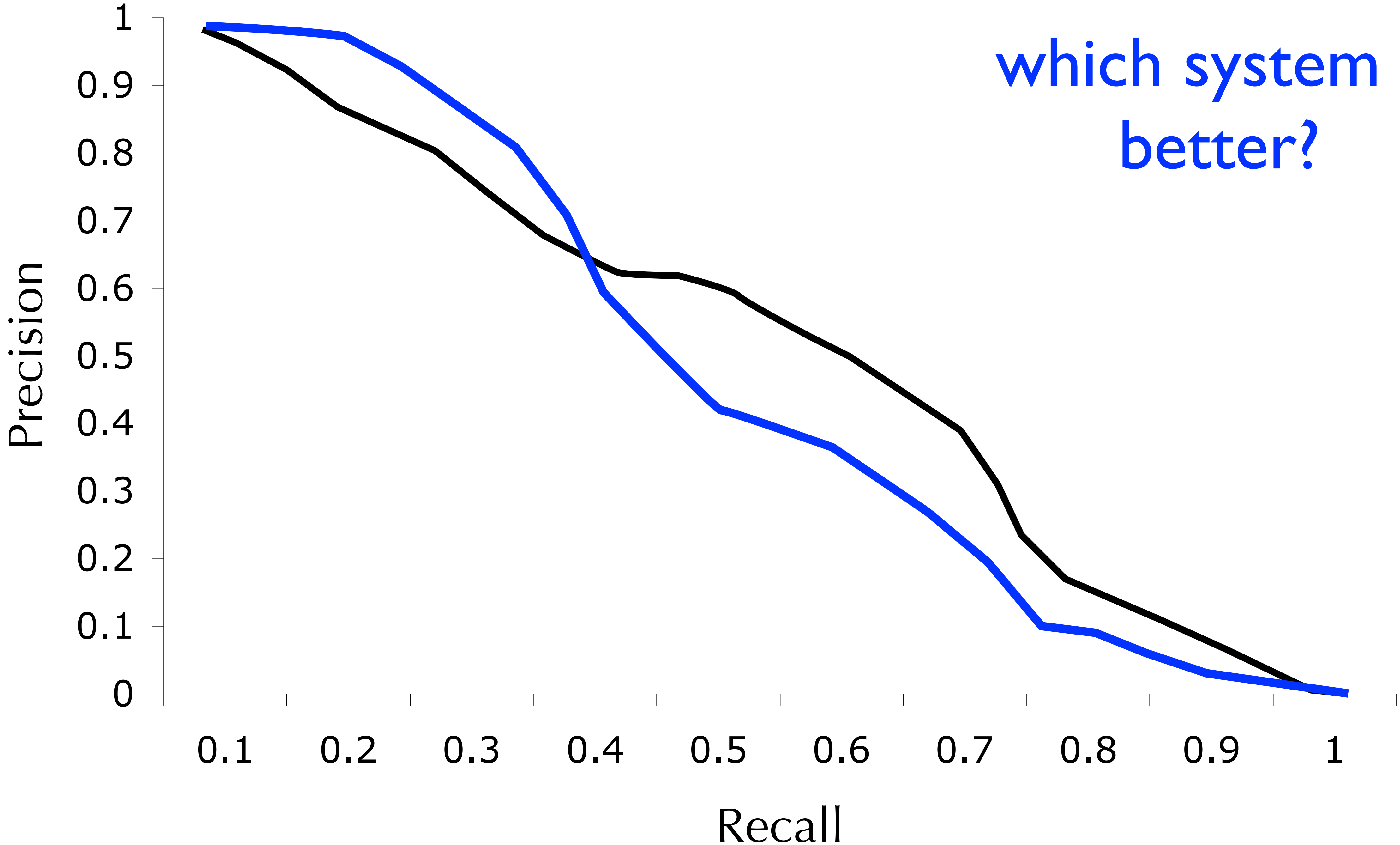
what level of recall should I expect if I want 0.9 precision?

Evaluation Metrics
(5) precision-recall curves



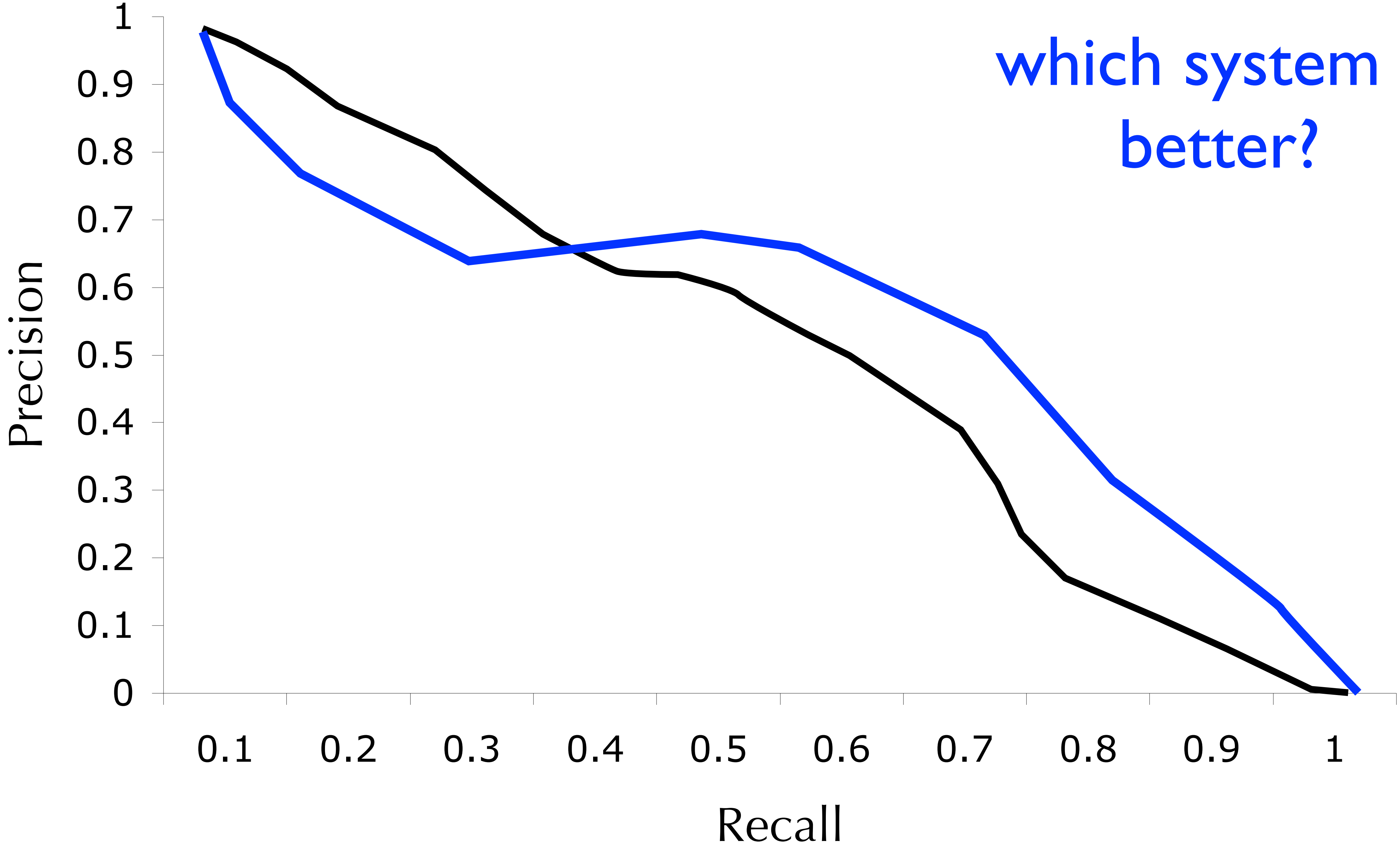
which system is better?

Evaluation Metrics
(5) precision-recall curves



which system is better?

Evaluation Metrics
(5) precision-recall curves

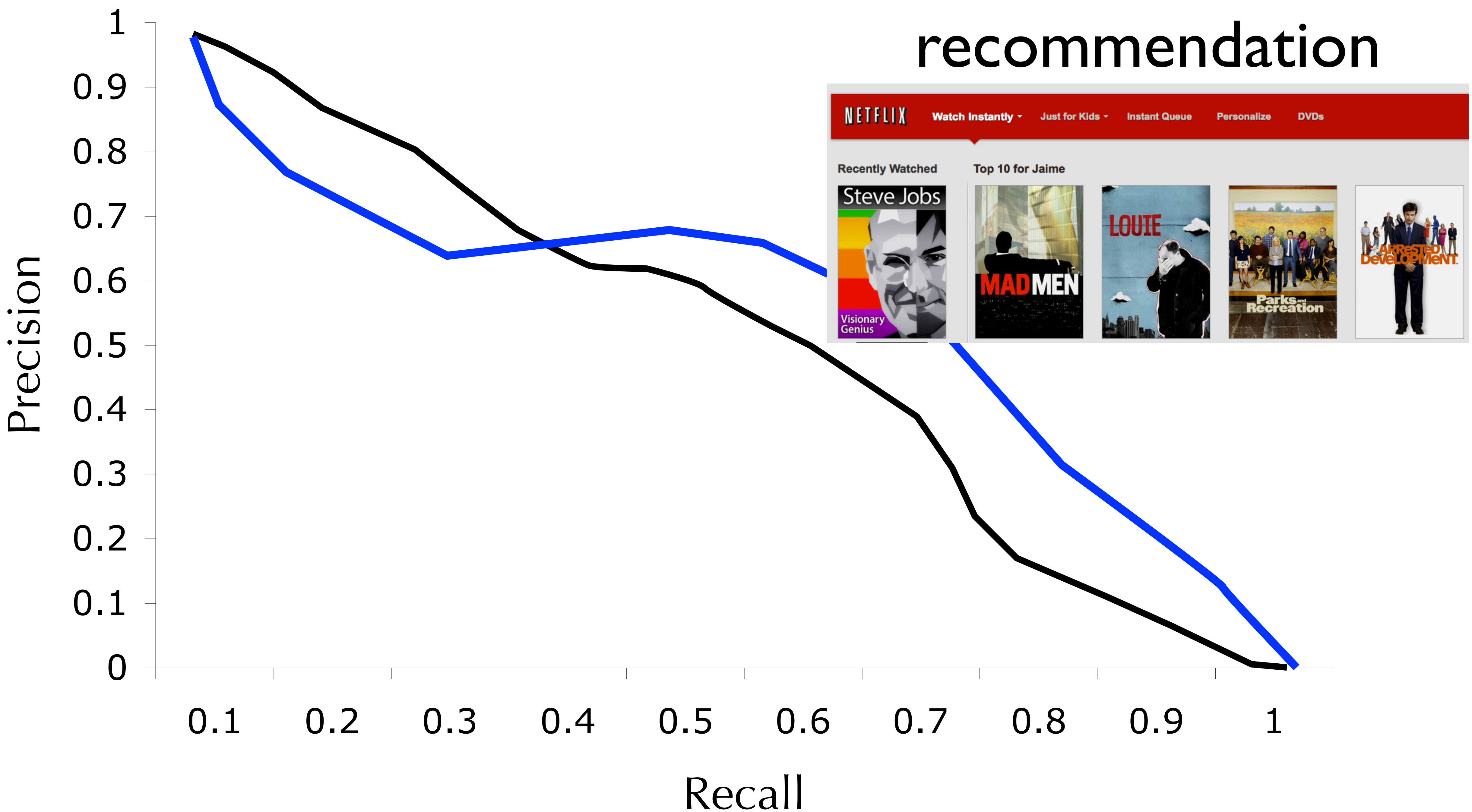


which system is better?

Evaluation Metrics

(5) precision-recall curves

content recommendation

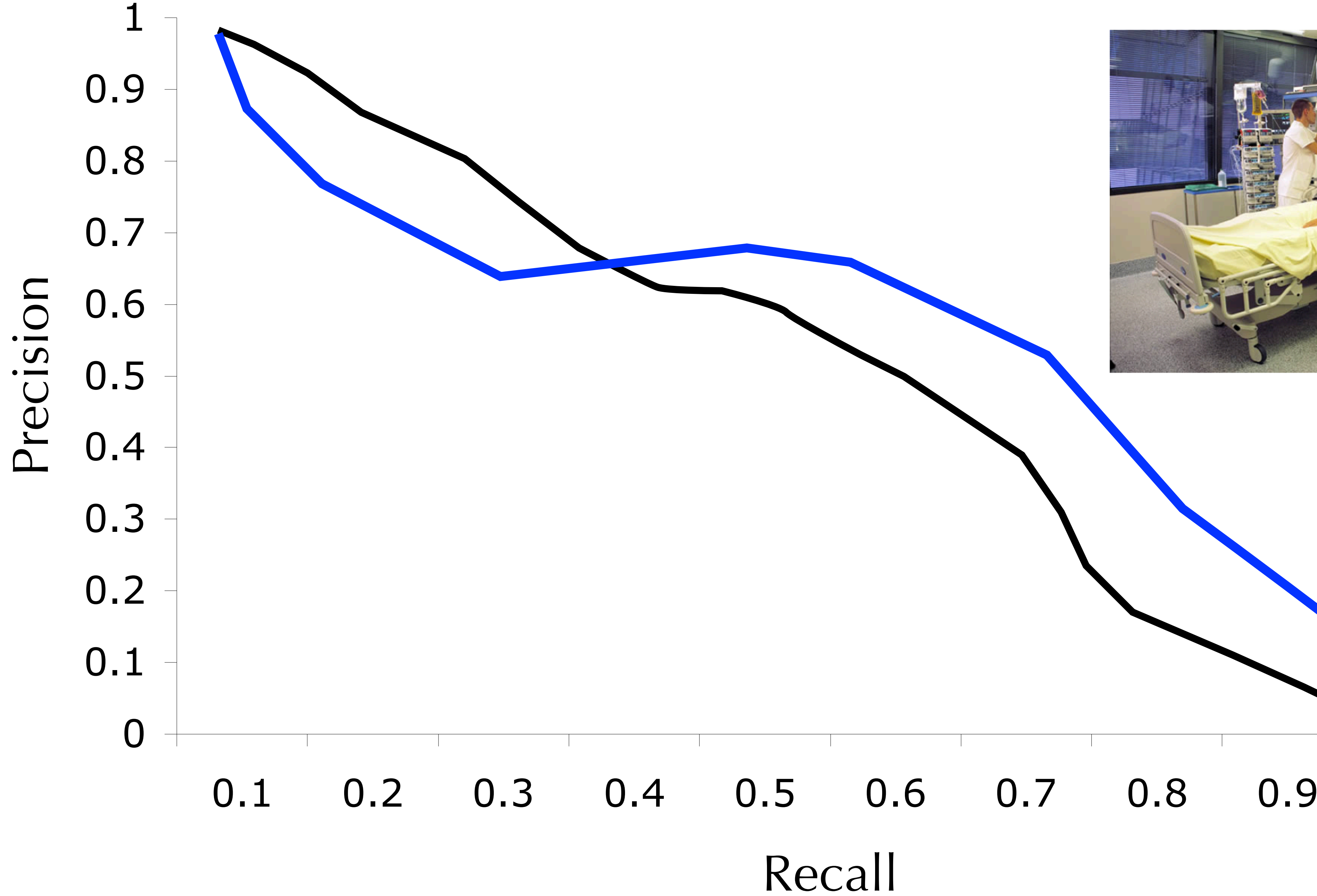


PR curves for ‘relevant’

Evaluation Metrics

(5) precision-recall curves

health monitoring



PR curves for 'alarm'

Evaluation Metrics

(5) precision-recall curves

- PR curves show different precision-recall operating points (or trade-off points)
- How many false positives will I have to sift through for a desired level of recall?
- How many true positives will I have to miss for a desired level of precision?

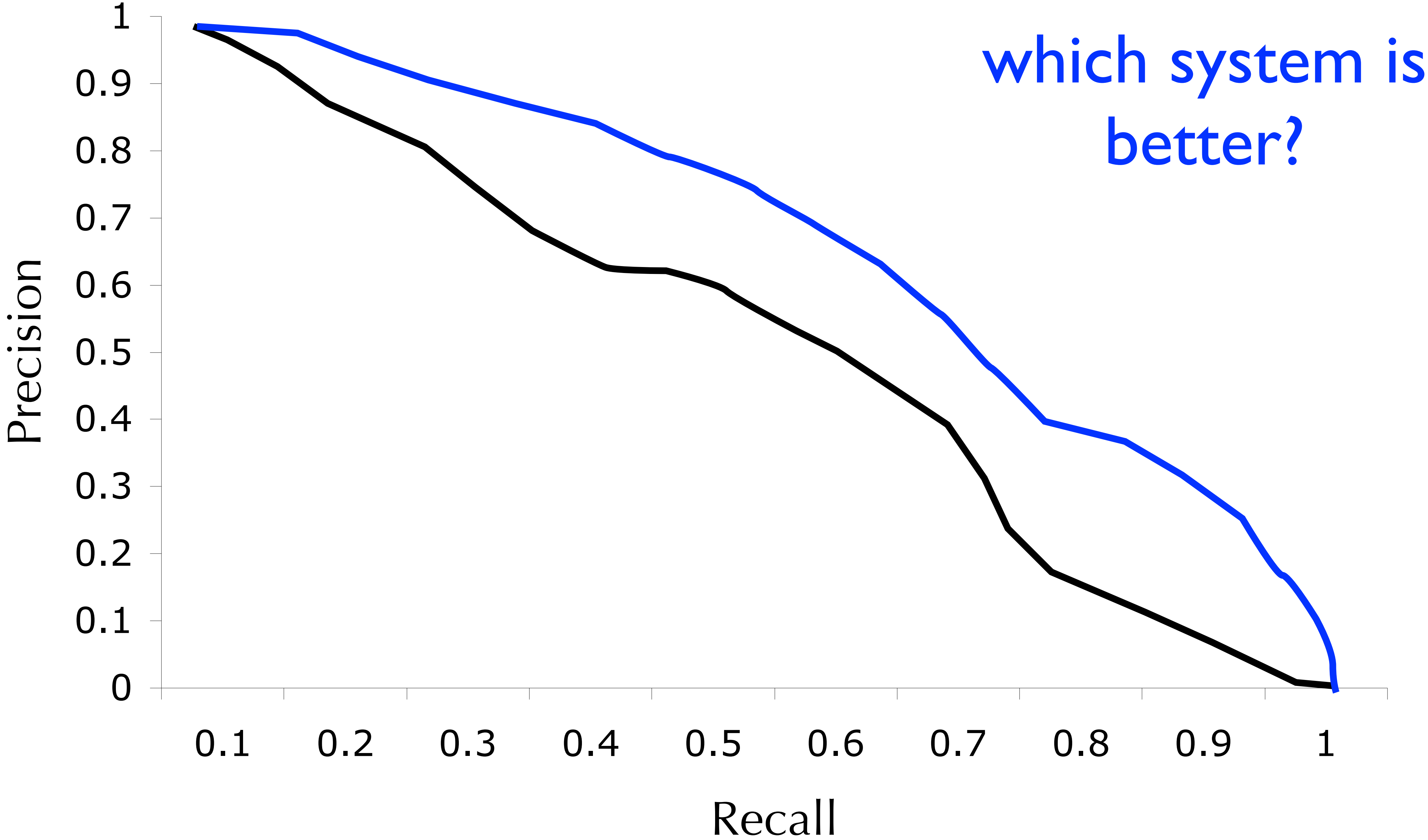
Evaluation Metrics

(6) average precision

- In some situations we may want to summarize the quality of a PR curve using a single number
  - when comparing across lots of different models or feature representations
- Average precision: <u>proportional</u> (not equal) to the area under the PR curve

Evaluation Metrics

(6) average precision



Evaluation Metrics

(6) average precision

- Average Precision
  1. Sort instances by descending order of confidence value
  2. Go down the ranking, and measure P@K <u>where recall increases</u>
  3. Take the average of all P@K values <u>where recall increases</u>

Evaluation Metrics

(6) average precision

rank (K)	ranking	P(POS|D)	P@K	R@K
1		0.99	1.00	0.10
2		0.87		
3		0.84	0.67	0.20
4		0.83	0.75	0.30
5		0.77	0.80	0.40
6		0.63	0.83	0.50
7		0.58	0.86	0.60
8		0.57		
9		0.56	0.78	0.70
10		0.34		
11		0.33	0.73	0.80
12		0.25		
13		0.21		
14		0.15	0.64	0.90
15		0.14		
16		0.14		
17		0.12		
18		0.08		
19		0.01		
20		0.01	0.50	1.00
		Average Precision	0.76	

Evaluation Metrics

(6) average precision

rank (K)	ranking	P(POS|D)	P@K	R@K
1		0.99	1.00	0.10
2		0.87	1.00	0.20
3		0.84	1.00	0.30
4		0.83	1.00	0.40
5		0.77	1.00	0.50
6		0.63	1.00	0.60
7		0.58	1.00	0.70
8		0.57	1.00	0.80
9		0.56	1.00	0.90
10		0.34	1.00	1.00
11		0.33		
12		0.25		
13		0.21		
14		0.15		
15		0.14		
16		0.14		
17		0.12		
18		0.08		
19		0.01		
20		0.01		
		Average Precision	1.00	

Evaluation Metrics

(6) average precision

rank (K)	ranking	P(POS|D)	P@K	R@K
1		0.99	1.00	0.10
2		0.87	1.00	0.20
3		0.84	1.00	0.30
4		0.83	1.00	0.40
5		0.77	1.00	0.50
6		0.63	1.00	0.60
7		0.58	1.00	0.70
8		0.57	1.00	0.80
9		0.56	1.00	0.90
10		0.34		
11		0.33	0.91	1.00
12		0.25		
13		0.21		
14		0.15		
15		0.14		
16		0.14		
17		0.12		
18		0.08		
19		0.01		
20		0.01		
		Average Precision	0.99	

Evaluation Metrics

(6) average precision

rank (K)	ranking	P(POS|D)	P@K	R@K
1		0.99	1.00	0.10
2		0.87	1.00	0.20
3		0.84	1.00	0.30
4		0.83	1.00	0.40
5		0.77	1.00	0.50
6		0.63	1.00	0.60
7		0.58	1.00	0.70
8		0.57	1.00	0.80
9		0.56	1.00	0.90
10		0.34	1.00	1.00
11		0.33		
12		0.25		
13		0.21		
14		0.15		
15		0.14		
16		0.14		
17		0.12		
18		0.08		
19		0.01		
20		0.01		
		Average Precision	1.00	

Evaluation Metrics

(6) average precision

rank (K)	ranking	P(POS|D)	P@K	R@K
1		0.99	1.00	0.10
2		0.87		
3		0.84	0.67	0.20
4		0.83	0.75	0.30
5		0.77	0.80	0.40
6		0.63	0.83	0.50
7		0.58	0.86	0.60
8		0.57	0.88	0.70
9		0.56	0.89	0.80
10		0.34	0.90	0.90
11		0.33	0.91	1.00
12		0.25		
13		0.21		
14		0.15		
15		0.14		
16		0.14		
17		0.12		
18		0.08		
19		0.01		
20		0.01		
		Average Precision	0.85	

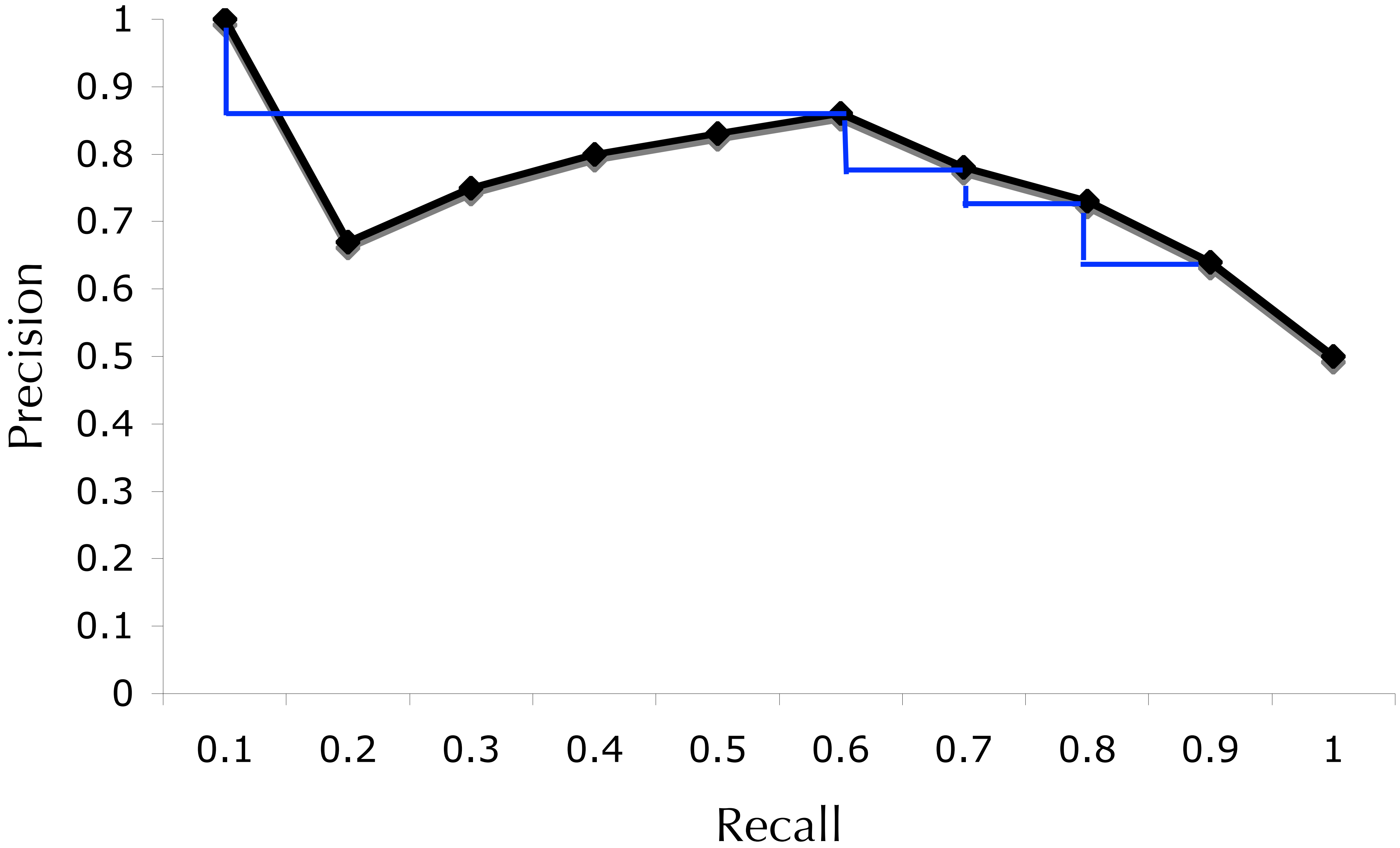
Evaluation Metrics

(6) average precision

rank (K)	ranking	P(POS|D)	P@K	R@K
1		0.99	1.00	0.10
2		0.87		
3		0.84	0.67	0.20
4		0.83	0.75	0.30
5		0.77	0.80	0.40
6		0.63	0.83	0.50
7		0.58	0.86	0.60
8		0.57		
9		0.56	0.78	0.70
10		0.34		
11		0.33	0.73	0.80
12		0.25		
13		0.21		
14		0.15	0.64	0.90
15		0.14		
16		0.14		
17		0.12		
18		0.08		
19		0.01		
20		0.01	0.50	1.00
		Average Precision	0.76	

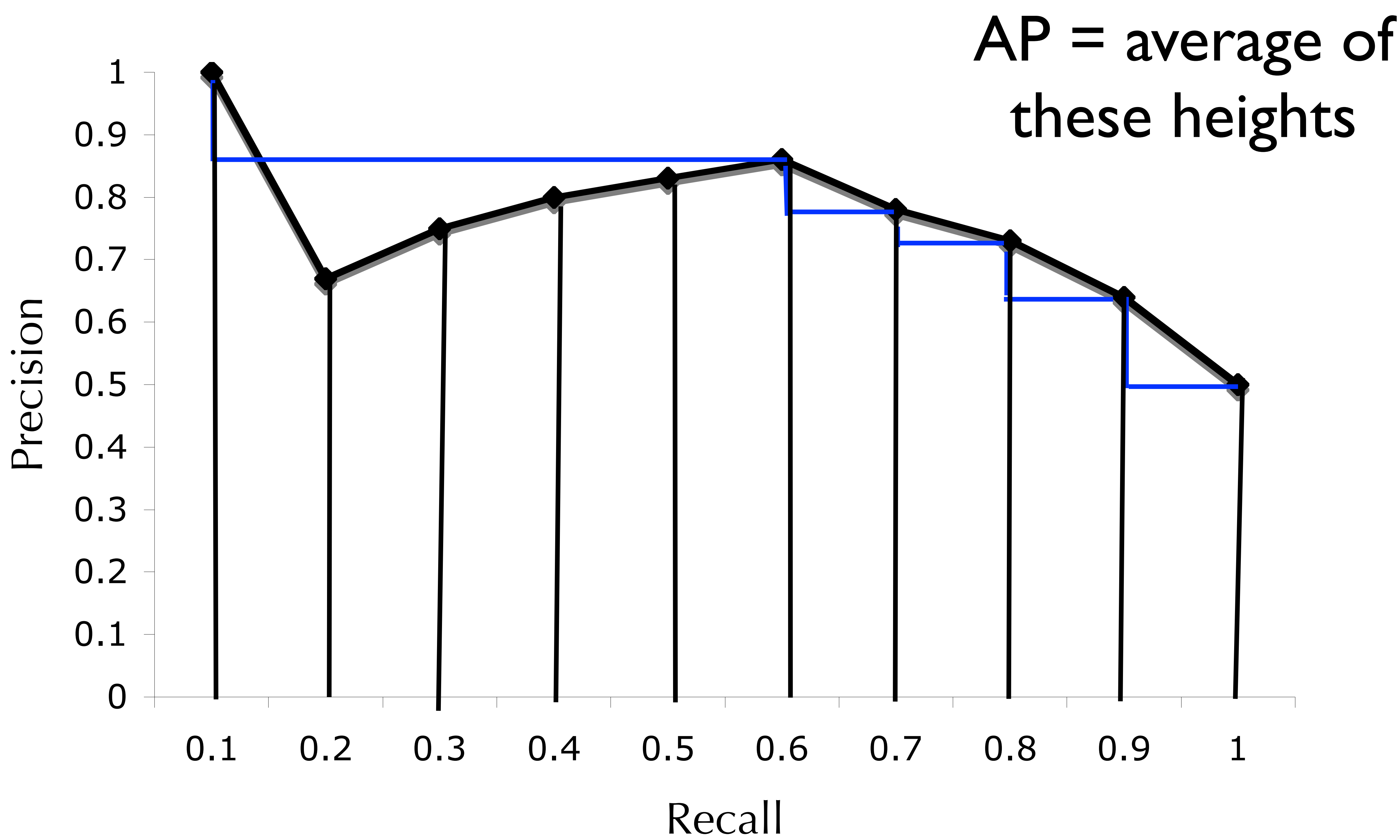
Evaluation Metrics

(6) average precision



Evaluation Metrics

(6) average precision



Evaluation Metrics

(6) average precision

- Average precision is proportional to the area under the PR curve
- It punishes high-confident mistakes more severely than low-confident mistakes

Evaluation Metrics

- Accuracy
- Precision
- Recall
- F-measure (or F1 measure)
- PR curves (not a metric, but rather a way to show different PR operating points)
- Average Precisions