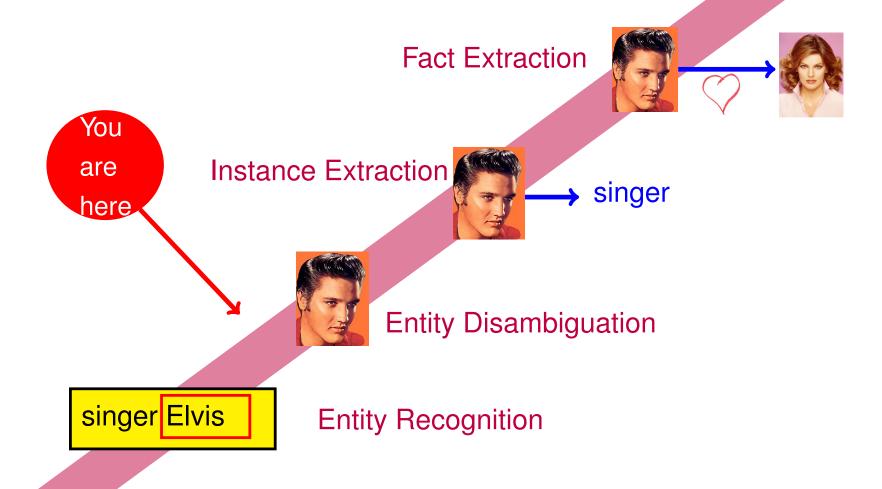
Evaluation

Fabian M. Suchanek

Semantic IE







Source Selection and Preparation

in The Simpsons, Homer Simpson is the father of Bart Simpson and Lisa Simpson. The M above his ear is for Matt Groening.



3

in The Simpsons, Homer Simpson is the father of Bart Simpson and Lisa Simpson. The M above his ear is for Matt Groening.



1. [A-Z][a-z]+ Simpson

in The Simpsons, Homer Simpson is the father of Bart Simpson and Lisa Simpson. The M above his ear is for Matt Groening.



1. [A-Z][a-z]+ Simpson

4 matches (1 wrong)

in The Simpsons, Homer Simpson is the father of Bart Simpson and Lisa Simpson. The M above his ear is for Matt Groening.



1. [A-Z][a-z]+ Simpson

4 matches (1 wrong)

2. [A-Z][a-z]+[A-Z][a-z]+

in The Simpsons, Homer Simpson is the father of Bart Simpson and Lisa Simpson. The M above his ear is for Matt Groening.



1. [A-Z][a-z]+ Simpson

4 matches (1 wrong)

2. [A-Z][a-z]+[A-Z][a-z]+

5 matches (2 wrong)

in The Simpsons, Homer Simpson is the father of Bart Simpson and Lisa Simpson. The M above his ear is for Matt Groening.



1. [A-Z][a-z]+ Simpson

4 matches (1 wrong)

2. [A-Z][a-z]+[A-Z][a-z]+

5 matches (2 wrong)

3. Homer Simpson

in The Simpsons, Homer Simpson is the father of Bart Simpson and Lisa Simpson. The M above his ear is for Matt Groening.



1. [A-Z][a-z]+ Simpson

4 matches (1 wrong)

2. [A-Z][a-z]+[A-Z][a-z]+

5 matches (2 wrong)

3. Homer Simpson

1 match

Def: Gold Standard

The gold standard (also: ground truth) for an IE task is the set of desired results of the task on a given corpus.

Task: Detect Simpson members

Corpus:

in The Simpsons, Homer Simpson is the father of Bart Simpson and Lisa Simpson. The M above his ear is for Matt Groening.

Gold Standard:

{Homer Simpson, Bart Simpson, Lisa Simpson}

The precision of an IE algorithm is the ratio of its outputs that are in the respective gold standard.

$$prec = \frac{|Output \cap GStandard|}{|Output|}$$

Output: {Homer, Bart, Groening}

The precision of an IE algorithm is the ratio of its outputs that are in the respective gold standard.

$$prec = \frac{|Output \cap GStandard|}{|Output|}$$

Output: {Homer, Bart, Groening}

The precision of an IE algorithm is the ratio of its outputs that are in the respective gold standard.

$$prec = \frac{|Output \cap GStandard|}{|Output|}$$

The precision of an IE algorithm is the ratio of its outputs that are in the respective gold standard.

$$prec = \frac{|Output \cap GStandard|}{|Output|}$$

The precision of an IE algorithm is the ratio of its outputs that are in the respective gold standard.

$$prec = \frac{|Output \cap GStandard|}{|Output|}$$

G.Standard: {Homer, Bart, Lisa, Marge}

=> Precision: 2/3 = 66%

The recall (also: sensitivity, true positive rate, hit rate) of an IE algorithm is the ratio of the gold standard that is output.

$$rec = \frac{|Output \cap GStandard|}{|GStandard|}$$

Output: {Homer, Bart, Groening}

The recall (also: sensitivity, true positive rate, hit rate) of an IE algorithm is the ratio of the gold standard that is output.

$$rec = \frac{|Output \cap GStandard|}{|GStandard|}$$

Output: {Homer, Bart, Groening}

The recall (also: sensitivity, true positive rate, hit rate) of an IE algorithm is the ratio of the gold standard that is output.

$$rec = \frac{|Output \cap GStandard|}{|GStandard|}$$

Output: {Homer, Bart, Groening}

The recall (also: sensitivity, true positive rate, hit rate) of an IE algorithm is the ratio of the gold standard that is output.

$$rec = \frac{|Output \cap GStandard|}{|GStandard|}$$

Output: {Homer, Bart, Groening}

The recall (also: sensitivity, true positive rate, hit rate) of an IE algorithm is the ratio of the gold standard that is output.

$$rec = \frac{|Output \cap GStandard|}{|GStandard|}$$

Output: {Homer, Bart, Groening}

The recall (also: sensitivity, true positive rate, hit rate) of an IE algorithm is the ratio of the gold standard that is output.

$$rec = \frac{|Output \cap GStandard|}{|GStandard|}$$

Output: {Homer, Bart, Groening}







Precision-Recall-Tradeoff

It is very hard to get both good precision and good recall.

Algorithms usually allowing varying one at the expense of the other (e.g., by choosing different threshold values). This usually yields:



Recall

Def: F1

To trade off precision and recall, we could use the average:

```
Gold Standard: {Homer, Bart, Lisa, Snowball_4, ..., Snowball_100} Output: {Homer Simpson}
```

Def: F1

To trade off precision and recall, we could use the average:

```
Gold Standard: {Homer, Bart, Lisa, Snowball_4, ..., Snowball_100}

Output: {Homer Simpson} Outputting just

Precision: 1/1=100%, Recall: 1/100=1% a single result

Average: (100%+1%)/2=50% already gives a score of 50%!
```

The F1 measure is the harmonic mean of precision and recall.

$$F1 = 2 \times \frac{precision \times recall}{precision + recall}$$

Precision: 1/1=100%, Recall: 1/100=1%

F1: 2×100%×1%/(100%+1%)=2%

Task: Precision & Recall

What is the algorithm output, the gold standard, the precision and the recall in the following cases?

1. Nostradamus predicts a trip to the moon for every century from the 15th to the 20th incl.

O{15,16,17,18,19,20} GS{20}

2. The weather forecast predicts that the next 3 days will be sunny. It does not say anything about the 2 days that follow. In reality, it is sunny during all 5 days. O{e1,e2,...,e15,o1,...,o5}

O{1,2,3} GS{1,2,3,4,5} GS{e1,e2,...,e90}

- 3.On Elvis RadioTM, 90% of the songs are by Elvis. An algorithm learns to detect Elvis songs. Out of 100 songs on Elvis Radio, the algorithm says that 20 are by Elvis (and says nothing about the other 80). Out of these 20 songs, 15 were by Elvis and 5 were not.
- 4. How can you improve the algorithm?

Imbalanced classes

```
Population: {Snowball_1,..., Snowball_99, Snowball_100} Gold Standard: {Snowball_1,..., Snowball_99} Output: {Snowball_1,..., Snowball_99, Snowball_100}
```

Def: Problem of imbalanced classes

```
Population: {Snowball_1,..., Snowball_99, Snowball_100}
```

Gold Standard: {Snowball_1,..., Snowball_99}

Output: {Snowball_1,..., Snowball_99, Snowball_100}

Precision: 99/100=99%

Recall: 99/99=100%

If there are very few negatives, just outputting all elements gives great scores.

The problem of imbalanced classes appears when only very few of the items of the population are not in the gold standard: An approach that outputs the entire population has a very high precison and a perfect recall.

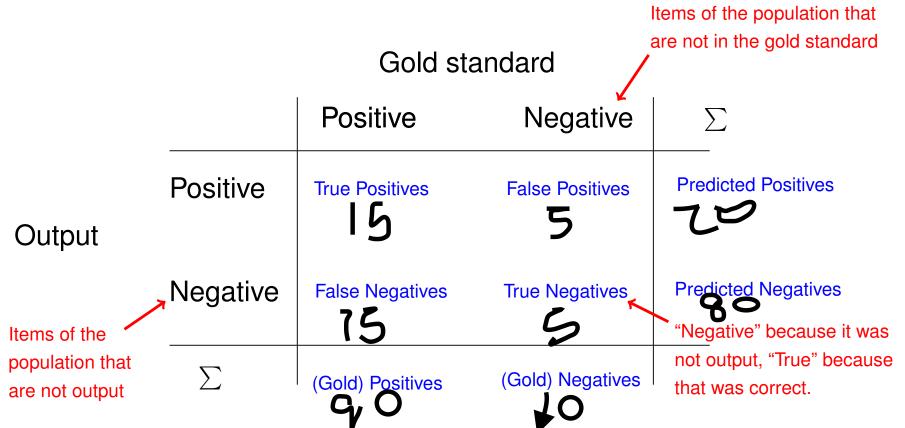
Def: Confusion Matrix

Population: {Snowball_1,..., Snowball_99, Snowball_100}

Gold Standard: {Snowball_1,..., Snowball_99}

Output: {Snowball_1,..., Snowball_99, Snowball_100}

The confusion matrix for the output of an algorithm looks as follows:



Def: Confusion Matrix

```
Population: {Snowball_1,..., Snowball_99, Snowball_100}
```

Gold Standard: {Snowball_1,..., Snowball_99}

Output: {Snowball_1,..., Snowball_99, Snowball_100}

The confusion matrix for the output of an algorithm looks as follows:

		Gold standard		1 item was output as positive, but was negative in the
		Positive	Negative	gold standard
Output	Positive	99	1	100
	Negative	0	0	0
		99	1	

Precision = true positives / predicted positives = 99/100 = 99%

Recall = true positives / gold positives = 99/99 = 100%

>ROC

Confusion with confusion matrixes

A confusion matrix does not always make sense in an information extraction scenario:

Population: {H, Ho, Hom, ..., o, om, ome, ..., r Sim, r Simps, ...}

Gold Standard: {Homer}

Output: {Homer}

Gold standard

Output

	Positive	Negative	
Positive	1	39462440205	39462440206
Negative	0	0	

A confusion matrix makes sense only when the population is limited (e.g., in classification tasks)!

Back to our problem

Population: {Snowball_1,..., Snowball_99, Snowball_100}

Gold Standard: {Snowball_1,..., Snowball_99}

Output: {Snowball_1,..., Snowball_99, Snowball_100}

Gold standard

Output

	Positive	Negative
Positive	99	1
Negative	0	0,

The problem is that the algorithm did not catch the negatives, it has a "low recall" on the negatives.

Def: True Negative Rate & FPR

```
Population: {Snowball_1,..., Snowball_99, Snowball_100}
```

Gold Standard: {Snowball_1,..., Snowball_99}

Output: {Snowball_1,..., Snowball_99, Snowball_100}

The true negative rate (also: TNR, specificity, selectivity) is the ratio of negatives that are output as negatives (= the recall on the negatives):

TNR = true negatives / gold negatives = 0 / 1 = 0%

Output

	Positive	Negative	
Positive	99	1	
Negative	0	0	

The False Positive Rate (also: FPR, fall-out) is 1-TNR.

TNR & Precision

Population: {Snowball_1,..., Snowball_99, Snowball_100}

Gold Standard: {Snowball_1,..., Snowball_99}

Output: {Snowball_1,..., Snowball_99, Snowball_100}

Precision: 99/100=99%

TNR: 0/1=0%

Recall: 99/99=100%

TNR and precision both measure the "correctness" of the output.

Precision:

- measures wrt. the output
- suffers from imbalanced classes
- works if population is infinite
 (e.g., set of all extractable entities)

TNR:

- measures wrt. the population
- guards against imbalance
- works if population is limited (e.g., in classification)

>ROC

Informedness

```
Population: {Snowball_1,..., Snowball_99, Snowball_100}
```

Gold Standard: {Snowball_1,..., Snowball_99}

Output: {Snowball_1,..., Snowball_99, Snowball_100}

Precision: 99/100=99%

TNR: 0/1=0%

Recall: 99/99=100%

The informedness (also: Youden's J statistic, Youden's index) combines

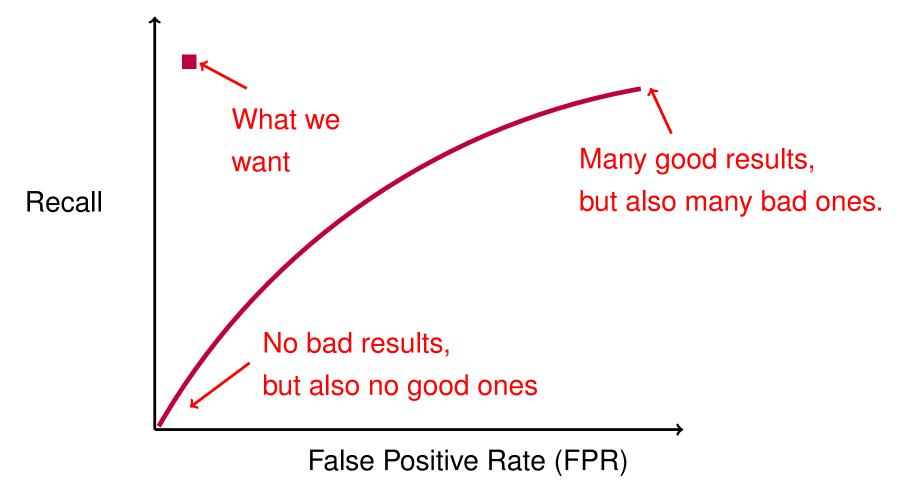
TNR and Recall as follows:

```
informedness = recall + TNR - 1 = recall - FPR = 100\% + 0\% - 1 = 0
```

(It's kind of the F1 measure in the case of a limited population.)

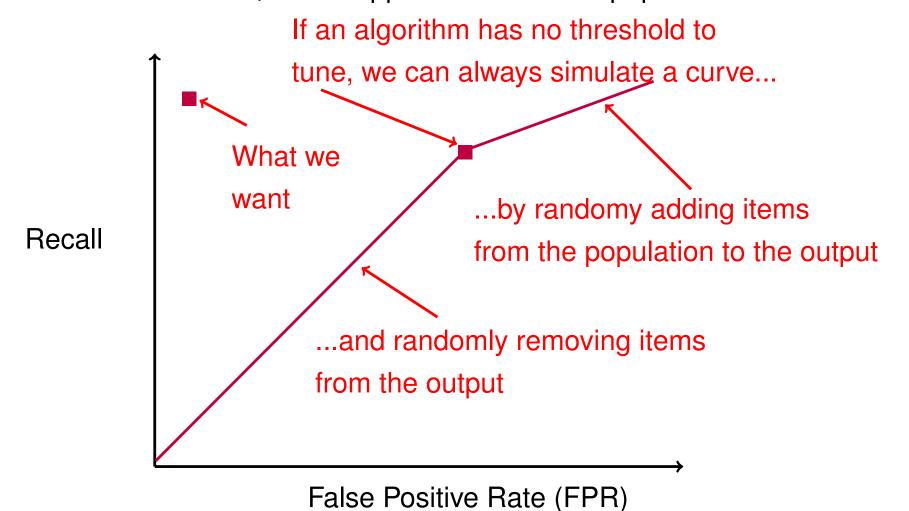
Def: ROC

The ROC (receiver operating characteristic) curve plots recall against the FPR for different thresholds of the algorithm. It guards against imbalanced classes, and is applicable when the population is finite.



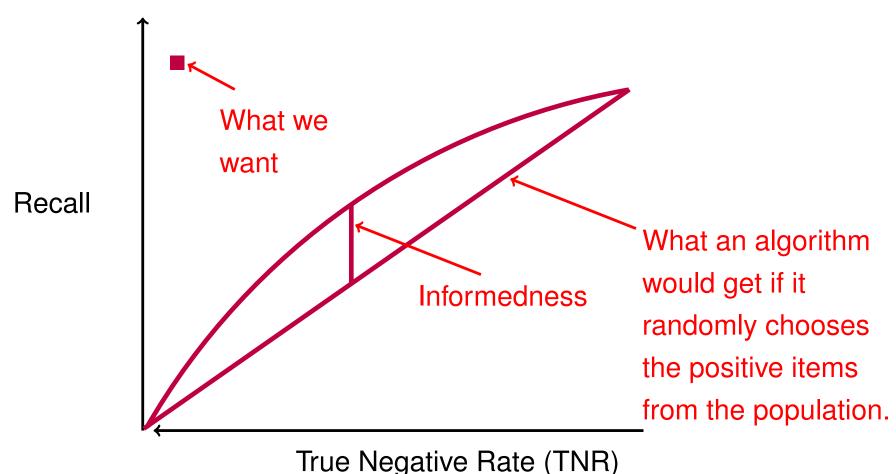
Def: ROC

The ROC (receiver operating characteristic) curve plots recall against the FPR for different thresholds of the algorithm. It guards against imbalanced classes, and is applicable when the population is finite.



Def: ROC

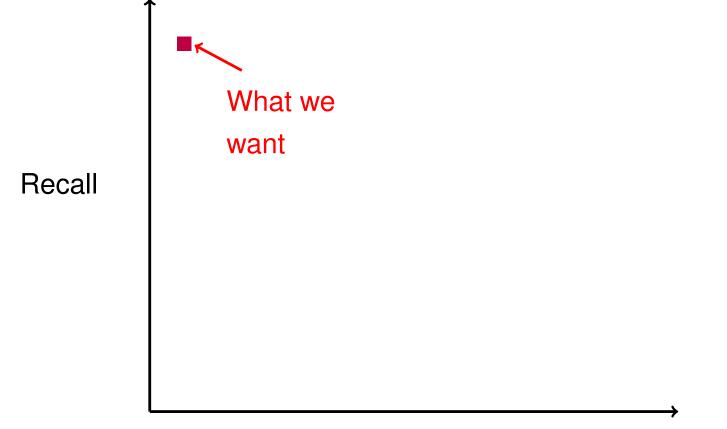
The ROC (receiver operating characteristic) curve plots recall against the FPR for different thresholds of the algorithm. It guards against imbalanced classes, and is applicable when the population is finite.



Def: AUC

The AUC (area under curve) is the area under the ROC curve.

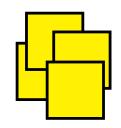
The AUC is between 0 and 1. A high AUC is good. Like F1, AUC combines recall and "correctness". AUC can be used when the population is known and finite. It guards againts unbalanced classes.



False Positive Rate (FPR)

Task: Find Simpson pets

Corpus:

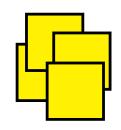




Algorithm: Regex "Snowball I*"

Task: Find Simpson pets

Corpus:



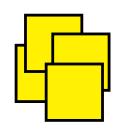


Output: {Snowball I, Snowball II}



Task: Find Simpson pets

Corpus:

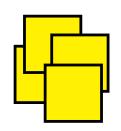






Task: Find Simpson pets

Corpus:



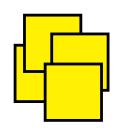


Output: {Snowball I,Snowball II,Snowball IV}



Task: Find Simpson pets

Corpus:



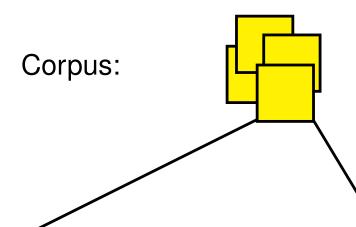


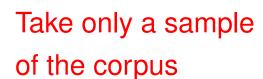
Output: {Snowball I,Snowball II,Snowball IV}

Is this algorithm good?



Task: Find Simpson pets

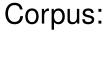




Lisa decides to play music on her saxophone for Coltrane, but the noise frightens him and he commits suicide.

As Gil swerves to avoid hitting Snowball V, his car hits a tree and bursts into flames. Since the cat is unhurt, Lisa takes it as a sign of good luck and adopts her. [...]

Task: Find Simpson pets

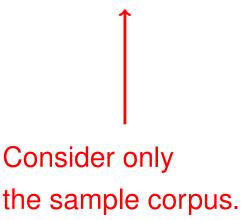




Consider only the sample corpus.







Gold Standard:

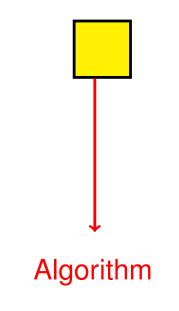
{Coltrane, Snowball I, ...}

Manually make a gold standard

Task: Find Simpson pets



Corpus:

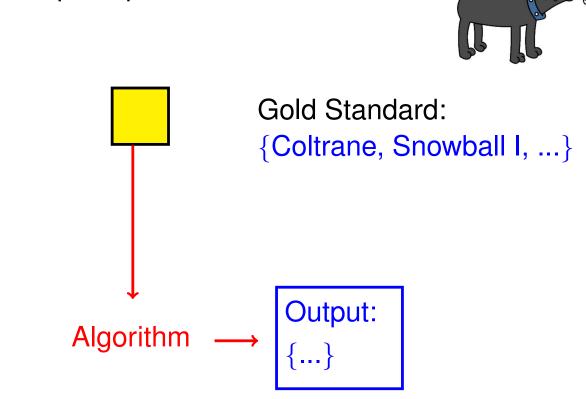


Gold Standard:

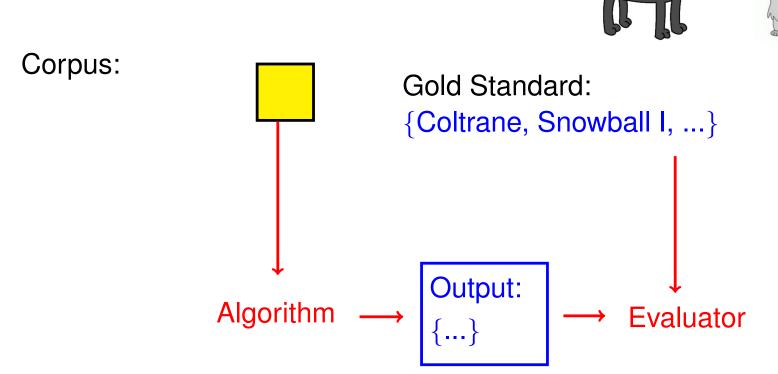
{Coltrane, Snowball I, ...}

Task: Find Simpson pets

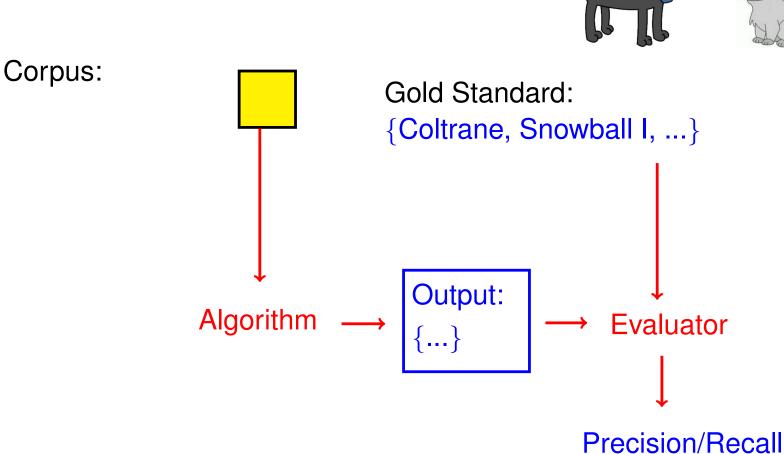
Corpus:



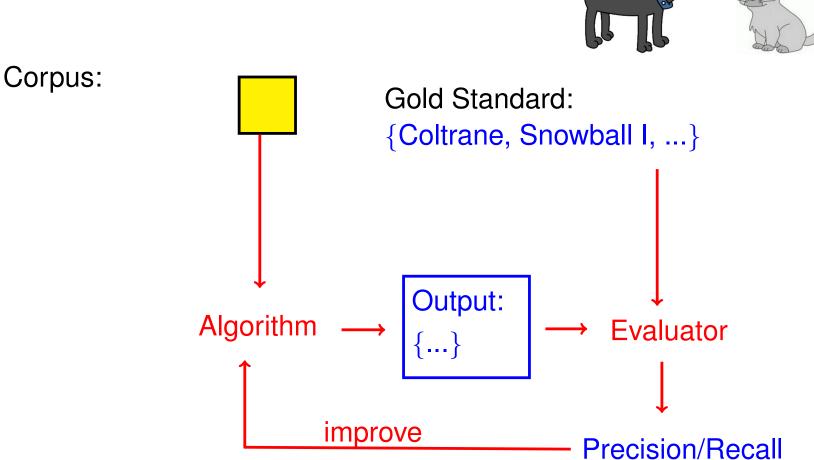
Task: Find Simpson pets



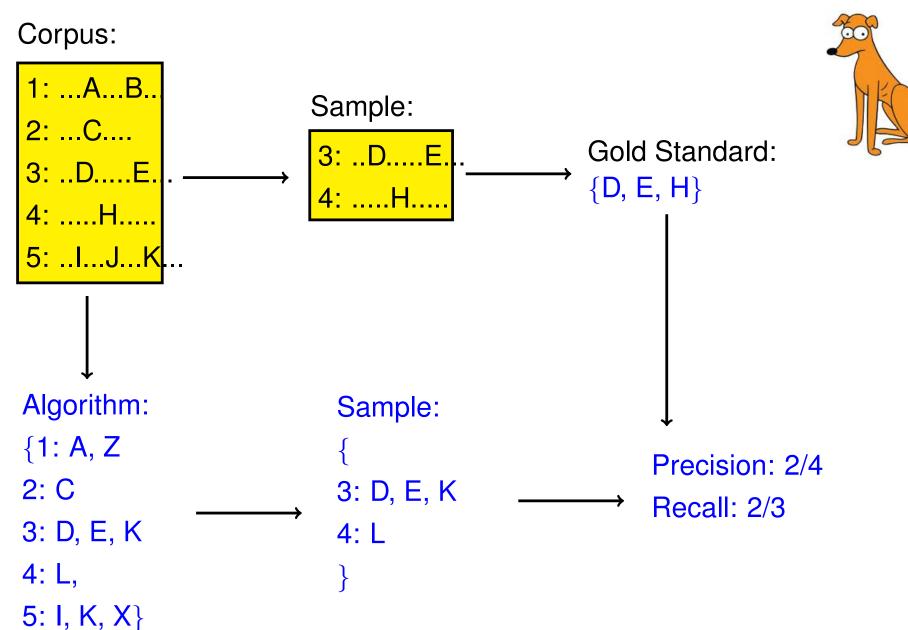
Task: Find Simpson pets



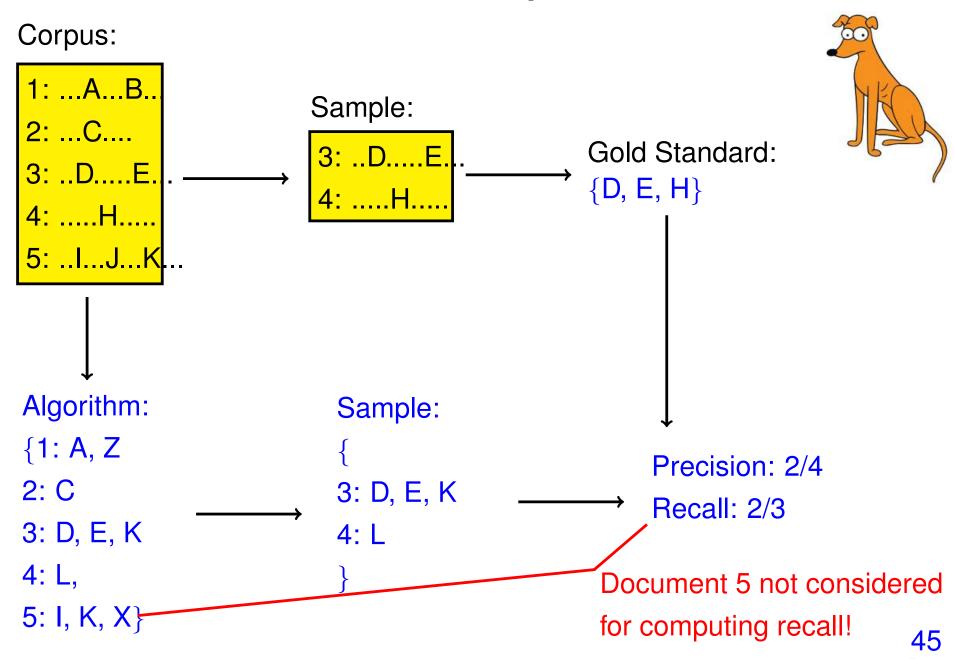
Task: Find Simpson pets



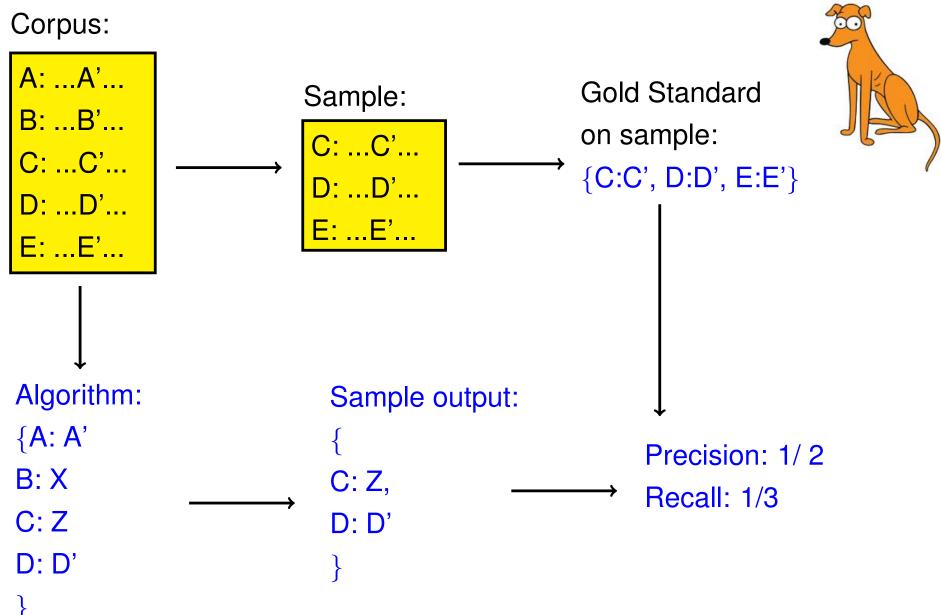
Evaluation on a Sample



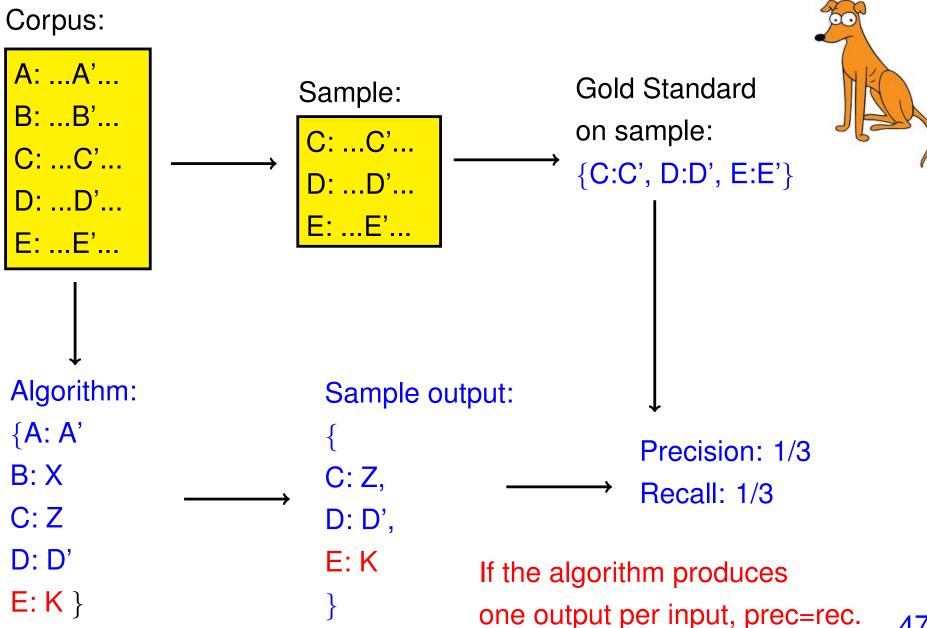
Evaluation on a Sample



Simple case: 1 target per document



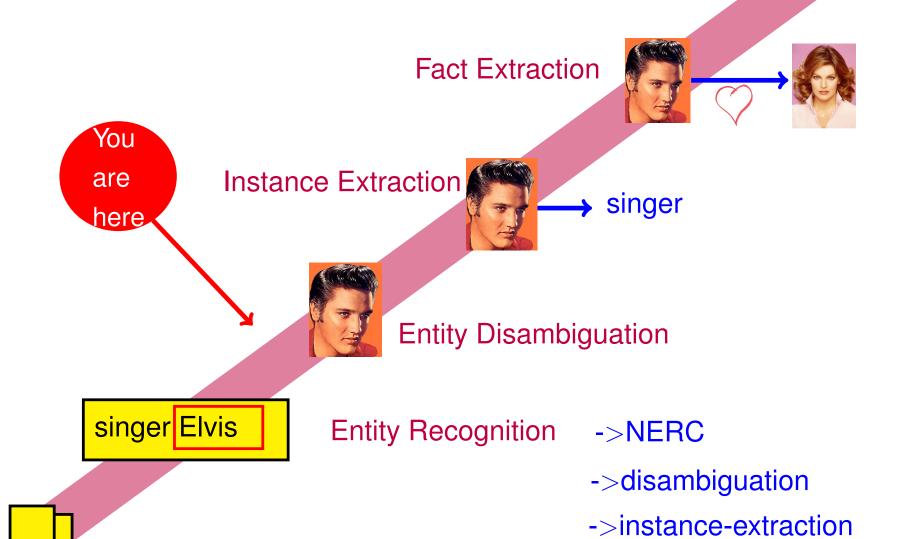
Simple case: 1 target per document



47

Semantic IE





Source Selection and Preparation