Language Understanding Systems

Evaluation in NLP

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Outline

1 Basic Concepts

2 Evaluation Metrics

3 Exercises





Section 1

Basic Concepts





Why do we want to evaluate a system / an algorithm's performance?



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• To measure one or more of its qualities.



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How do we evaluate a system / an algorithm's performance?





Automatic Evaluation

Compare the system's output with the gold standard (reference)



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OBJECTIVE

Manual Evaluation

Ask human judges to estimate the quality w.r.t. certain criteria

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SUBJECTIVE





Intrinsic vs. Extrinsic Evaluation

Intrinsic

- in isolation
- w.r.t. gold standard (references)
- e.g. POS-Tagging performance





Intrinsic vs. Extrinsic Evaluation

Intrinsic

- in isolation
- w.r.t. gold standard (references)
- e.g. POS-Tagging performance

Extrinsic

- as a part of other system
- usefulness for some other task
- e.g. effect of POS-Tagger on parsing performance





Black-Box vs. Glass-Box

Black-Box

Evaluation of Performance

- speed
- accuracy
- etc.





Black-Box vs. Glass-Box

Black-Box

Evaluation of Performance

- speed
- accuracy
- etc.

Glass-Box

Evaluation of Design

- algorithm
- used resources
- etc.





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- Annotation by experts (human judges)
- How do we know that Gold Standard is good?
- Evaluate agreement between the annotators/judges
- Most simple agreement measure: % of agreed instances





Lower & Upper Bounds of the Performance

Lower Bound

Baseline – trivial solution to the problem:

- random: random decision
- *chance*: random decision w.r.t. the distribution of categories in the training data
- majority: assign everything to the largest category
- etc.





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Upper Bound

Inter-rater agreement – human performance.



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- etc.

Upper Bound

Inter-rater agreement – human performance.

A system is expected to perform within the lower and upper bounds.



Data Split

Training for training / extracting rules / etc.

Development for optimization / intermediate evaluation

Testing for the final evaluation



Section 2

Evaluation Metrics





The Simplest Case

$$Accuracy = \frac{\text{Num. of Correct Decisions}}{\text{Total Num. of Instances}} \tag{1}$$





The Simplest Case

$$Accuracy = \frac{\text{Num. of Correct Decisions}}{\text{Total Num. of Instances}} \tag{1}$$

- Known number of instances
- Single decision for each instance
- Single correct answer for each instance
- All errors are equal





Contingency Table

		\mathbf{REF}	
		POS	NEG
HYP	POS	TP	FP
	NEG	FN	TN



Contingency Table

		\mathbf{REF}	
		POS	NEG
НҮР	POS	TP	FP
	NEG	FN	TN

```
TP True Positive a
FP False Positive b
FN False Negative c
TN True Negative d
```



Accuracy

		\mathbf{REF}	
		POS	NEG
HYP	POS	\mathbf{TP}	\mathbf{FP}
	NEG	$\mathbf{F}\mathbf{N}$	TN

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{2}$$



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• What if TN is infinite or unknown?



Accuracy

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$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{2}$$

- What if TN is infinite or unknown?
- e.g.: Number of irrelevant queries to a search engine





Precision & Recall

		\mathbf{REF}		
		POS	NEG	
HYP	POS	TP	FP	Precision
	\overline{NEG}	$\mathbf{F}\mathbf{N}$	TN	
		Recall		

$$Precison = \frac{TP}{TP + FP} \tag{3}$$



Precision & Recall

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HYP	POS	TP	\mathbf{FP}	Precision
	\overline{NEG}	$\mathbf{F}\mathbf{N}$	TN	
		Recall		

$$Precison = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

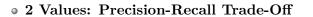


Precision & Recall

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F-Measure

• Harmonic Mean of Precision & Recall



F-Measure

- Harmonic Mean of Precision & Recall
- Usually evenly weighted

$$F_{\beta} = \frac{(1+\beta^2) * Precision * Recall}{\beta^2 * Precision + Recall}$$
 (5)

$$F_1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{6}$$





Edit Distance

- Hypotheses and Reference might differ not only on instance labels, but also on number of instances
- Number of concepts





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- WER: Word Error Rate
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$$*ER = \frac{I + D + S}{N} \tag{7}$$





More Advanced Topics

- Cross-Validation
- Significance Tests
- Agreement Measures
- Sampling (random, stratified)
- Binary vs. Multi-class classification
- Multi-label data
- Regression
- Re-ranking
- Ensemble Methods
- etc.





Section 3

Exercises





Exercises

Given the sample data, where Column 1 – References and Column 2 – Hypotheses:

- 1 Compute raw TP, FP, FN, TN.
- 2 Compute Accuracy, Precision, Recall, F-Measure



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Write scripts...



Synthetic Data

- Generate a Data Set where:
 - 5 classes
 - the distribution is 20%, 20%, 30%, 25%, 5%
- Sampling:
 - Split into training and test sets as 90% & 10%
 - Random vs. Stratified Sampling



