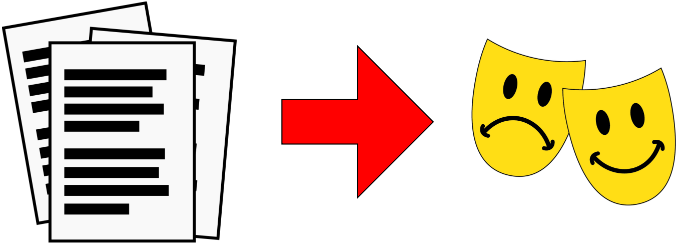
Evaluating Machine Translation Systems

Daniel Beck

May 22, 2017

Sentiment Analysis



Evaluating Text Classifiers

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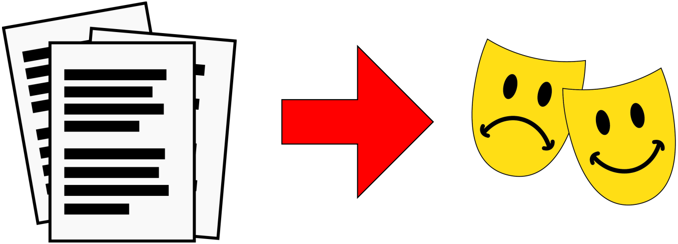

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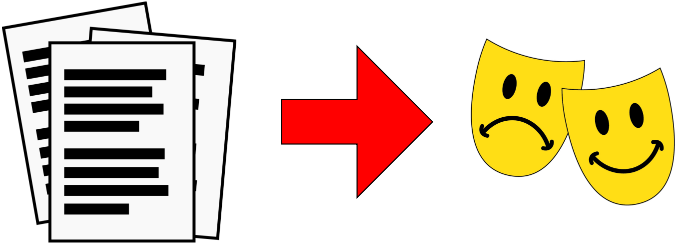

- Evaluation is easy: just count errors on a test set.
- Accuracy, Precision, Recall, F-measure.

Evaluating Sequence Labellers

Part-of-speech Tagging

Input:	I	saw	her	duck
Output:	PRON	VERB	PRON	VERB
Truth:	PRON	VERB	DET	NOUN

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- Evaluation is similar to classification.
- Count mistakes at the token level and use the same metrics.

Machine Translation Evaluation

这个 机场 的 安全 工作 由 以色列 方面 负责 .

Israeli officials are responsible for airport security.
Israel is in charge of the security at this airport.
The security work for this airport is the responsibility of the Israel government.
Israeli side was in charge of the security of this airport.
Israel is responsible for the airport's security.
Israel is responsible for safety work at this airport.
Israel presides over the security of the airport.
Israel took charge of the airport security.
The safety of this airport is taken charge of by Israel.
This airport's security is the responsibility of the Israeli security officials.

[Koehn, 2010, Figure 8.1]

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Evaluation is hard!

A single sentence can admit multiple translations.

1. Manual Evaluation

2. Automatic Evaluation
   - Intrinsic metrics
   - Trained Metrics
   - Evaluating metrics

3. Task-based Evaluation

Manual Evaluation - Direct Assessment

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Prone to noise and scaling biases

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- Less information about the **absolute** quality of an MT system but is easier for the judges and more consistent. Useful to compare systems between themselves.
- Can also be done in more fine-grained ways, using aspects such as adequacy and fluency.

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We usually want quick and cheap ways to assess quality when building MT systems, especially when **tuning** these systems.

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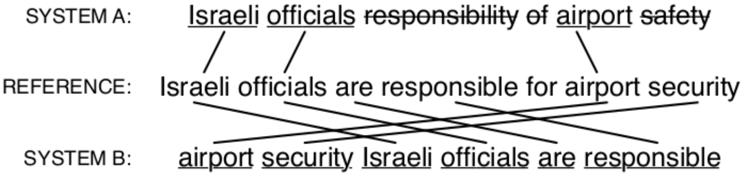
- Design a metric that **mimics** human evaluation as close as possible...
- ...while also being cheap and fast.

Word Matches

Count word matches and apply classification metrics.



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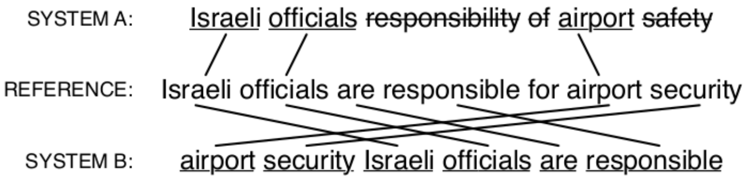

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	Precision	Recall	F-measure
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System B	1.0	0.86	0.92

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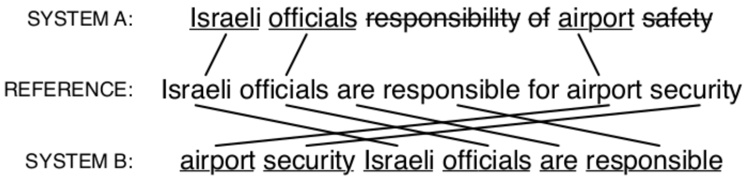

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Problem: metrics are agnostic to **word order**

Word Error Rate

We can take word order into account by using Word Error Rate (WER), which is based on the **edit distance** between strings.

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Problem: sometimes the word order requirement is too harsh

- Reference: "Israeli officials are responsible for airport security"
- Output: "This airport's security is responsibility of the Israeli security officials"
- WER: 1.29

BLEU - A Compromise

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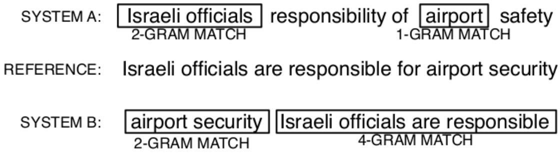

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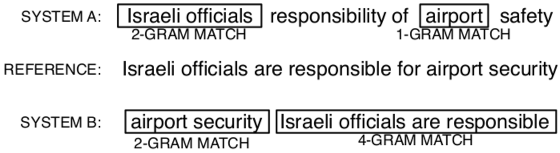

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	System A	System B
1-gram	3/6	6/6
2-gram	1/5	4/5
3-gram	0/4	2/4
4-gram	0/3	1/3

BLEU

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- BLEU takes advantage of that: all precisions are calculated with respect to the **whole test set** T.

$$precision_n = \frac{\sum_{s \in T} \sum_{\text{n-gram}} Match(\text{n-gram})}{\sum_{s \in T} \sum_{\text{n-gram}} Count(\text{n-gram})}$$

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BLEU introduces a brevity penalty term to penalise short translations, resulting in the formula:

$$\text{BLEU} = \min\left(1, \frac{\textit{output length}}{\textit{reference length}}\right) \prod_{n=1}^{4} \textit{precision}_n$$

Other Metrics

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METEOR [Banerjee and Lavie, 2005]

- Similar to BLEU but with focus on recall
- Also allow **soft** matches, using word stems, synonyms and paraphrases

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Idea: use the data to **learn** a metric in a supervised learning setting.

- Inputs: MT output and reference translation
- Output: score (usually the higher, the better)

BEER

BEER [Stanojević and Sima'an, 2014] is a trained metric that uses a linear model. Given an MT output o and a reference r, it is defined as:

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- $\mathbf{w}$ is a set of weights.
- $\phi_{o,r}$ is a set of features that compare o with r:
  - Word and character-level matches.
  - Word order features, obtained by counting permutations.

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This is just binary classification! BEER uses logistic regression but other algorithms could be used as well.

Evaluating Metrics

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- A perfect automatic metric would simulate manual evaluation
- We can assess a metric by its **correlation** with human judgements

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- A score of 1 gives perfect agreement, -1 gives perfect disagreement and 0 means no correlation.

Kendall's τ

Direction	en-fr	en-de	en-hi	en-cs	en-ru
BEER	**.295**	**.258**	.250	**.344**	**.440**
METEOR	.278	.233	.264	.318	.427
AMBER	.261	.224	**.286**	.302	.397
BLEU-NRC	.257	.193	.234	.297	.391
APAC	.255	.201	.203	.292	.388

Table 3: Kendall τ correlations on the WMT14 human judgements when translating out of English.

[Stanojević and Sima'an, 2014]

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- No reference translations!
- No human judgements!

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All these tasks can be measured in some way

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- Main goal is to predict quality at **test time**, when the system is used in production.
- Idea is similar to trained metrics: we collect data and train supervised ML models.
  - Except that we have no access to reference translations.
  - And the labels are directly related to end tasks.

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Metric choice depends on the application. For instance, post-editing time can be useful not only for quality prediction but also to give productivity estimates.

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  - Source sentence length;
  - MT output length;
  - Language model probabilities;
  - Word alignment scores;
  - ...

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Some recent work try to tackle these problem.s

- Learning from multiple users [Cohn and Specia, 2013].
- Uncertainty estimates for predictions [Beck et al., 2016].

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Further reading: [Koehn, 2010, Chap. 8]

Banerjee, S. and Lavie, A. (2005).
METEOR: An automatic metric for MT evaluation with improved correlation with human judgments.
Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization, (June):65.

Beck, D., Specia, L., and Cohn, T. (2016).
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