Machine Translation Evaluation: Manual Vs Automatic - A Comparative Study

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Machine Translation and MT Evaluation

Definition

Machine Translation(MT) deals with the conversion of natural language texts from one language to another using computers.[1]

Definition

Machine Translation Evaluation deals with judging how good an MT system is[7].

- The evaluation of machine translation is a fundamentally hard problem, since it relates to the unresolved problem of semantic equivalence[7]

Manual Vs Automatic

Manual	**Automatic**
Done by a human well versed in both source and target language	Done by comparing the MT output with reference translations
Humans judge whether meaning is preserved or not directly	Do not attempt to judge meaning directly[4]
Expensive, time consuming and subjective	Inexpensive and quick; useful for tracking progress of an MT systems on fixed data set; for comparing different MT systems
Scores are reliable	Scores may not be meaningful
Metrics: *Adequacy, Fluency , Intelligibility, Fidelity[11]*	Metrics: BLEU[8], NIST[6], METEOR[1], WER[10] & TER[9]

Manual Evaluation Metrics

Metric	Underlying Idea
Adequacy	How well the meaning is captured in translation (TL)
Fluency	How fluent translation is in TL
Intelligibility	How understandable the text is in TL
Fidelity or Accuracy	How much information is retained in the TL
Task-oriented[12]	Judge whether an MT system is suitable for tasks like comprehension, extraction, etc.
Segment ranking[3]	Ranking outputs from various MT systems

Automatic Evaluation Metrics

Metric	Underlying Idea
BLEU	Geometric mean of modified n-gram precision with brevity penalty
NIST	Variant of BLEU with weighted n-gram precision and modified brevity penalty
METEOR	Harmonic mean of Precision and Recall of uni-gram as well as approximate matches (stem, synonyms etc.), using linguistic resources like steamers, Word-net, etc.
METEOR-Hindi	Modified METEOR metric which uses Hindi related resources
WER	Min number of edit operations required to transfer a MT output into a reference translation
TER	Same as WER with additional shift edit

Questions We Wanted To Ask

1. How well do the automatic scores correlate with manual scores?
2. What is the distribution of manual scores for a given interval of automatic scores?
3. Can we estimate the manual metric score for a given automatic metric score?

Choice of Metrics

Manual Metrics

- Checking if meaning is preserved or not is more important
- Therefore, we chose **Adequacy** over **Fluency**

Adequacy: how well translated sentence convey same meaning as input sentence? is phrase or part of text is distorted, added or lost?[7]

Scores	Adequacy
5	all meaning is preserved
4	most meaning is preserved
3	much meaning is preserved
2	little meaning is preserved
1	none of the meaning is preserved

Table: Manual Metric: Adequacy

Automatic Metrics

- BLEU, NIST, METEOR, WER and TER

Data and MT Systems Detail

- Translation direction: English to Hindi
- WMT14[2] published 2507 test sentences with reference translations - we randomly selected 450 sentences from this dataset
- Translation outputs considered from 3 different systems:Online-B[*][1], IIT-BOMBAY[10] and MANAWI-RMOOVE(MR)[11][2]
- Data: 450 x 3 = 1350 <source, reference, system-output> triples

[1] [*]. No exact citation is found for this system because translation outputs are collected by WMT14 organizing committee

[2] ranked 1, 5 and 9 respectively in the shared task WMT14 for English Hindi

Manual Evaluation

- Done by 9 bilingual annotators
- Each annotator evaluates 300 sentences in two rounds: 150 sentences per round
- Each will get equal proportions from all 3 MT systems
- Every system-output will be annotated by exactly 2 annotators (for getting inter-annotator agreement)
- Average of scores from two annotators is considered for further experiments

Inter Annotator Agreement - Kappa Coefficient (k)

Kappa coefficient (k)[5]

$$k = \frac{P(A) - P(E)}{1 - P(E)}$$

Where,
P(A): proportion of times the annotators agree
P(E): proportion of times they would agree by chance

Kappa	**Agreement**
< 0	Less than chance agreement
0.01 - 0.20	Slight agreement
0.21 - 0.40	Fair agreement
0.41 - 0.60	Moderate agreement
0.61 - 0.80	Substantial agreement
0.81 - 0.99	Almost perfect agreement
1	Perfect agreement

MT System	**#Sentences**	**k-Values**
Online-B	450	0.2366
IIT-Bombay	450	0.2327
MANAWI-RMOOVE	450	0.2821
All Systems	1350	0.2884

Table: Kappa coefficient interpretation and K-values for inter annotator agreement

Our results of inter annotator agreement are similar to WMT14.

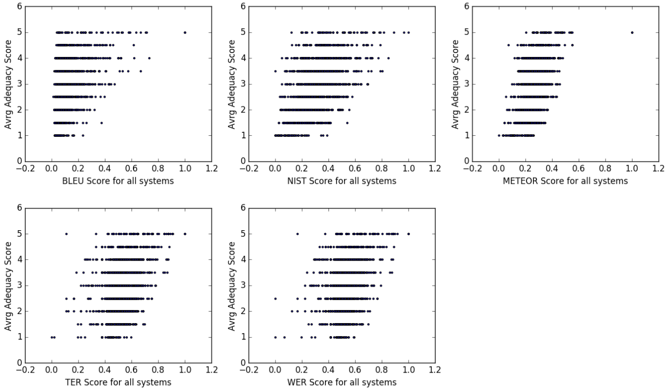
Automatic Evaluation

- Automatic metric scores are computed for all 1350 (450X3) system outputs
- Scores are obtained using open source tools[3] [4] [5]

[3] BLEU and NIST: https://github.com/moses-smt/mosesdecoder/blob/master/scripts/generic/mteval-v13a.pl
[4] METEOR: http://www.cs.cmu.edu/ alavie/METEOR/
[5] TER and WER: http://www.cs.umd.edu/ snover/tercom/

Correlation:Best Automatic Metric

- We find the best automatic metric using correlation scores between average human judgment(adequacy score) and automatic metric scores.
- higher the correlation score better the metric is.



Pearson's correlation coefficient(ρ)[13]

$$\rho = \frac{\Sigma_{i=1}^{n}(H_i - \bar{H})(M_i - \bar{M})}{\sqrt{\Sigma_{i=1}^{n}(H_i - \bar{H})^2}\sqrt{\Sigma_{i=1}^{n}(M_i - \bar{M})^2}}$$

where,
H_i: manual evaluation score of segment i
M_i: automatic evaluation score of segment i
$\bar{H}$: average of manual scores
$\bar{M}$: average of automatic scores

Correlation	Negative	Positive
small	-0.29 to -0.10	0.10 to 0.29
medium	-0.49 to -0.30	0.30 to 0.49
large	-1.00 to -0.50	0.50 to 1.00

Metrics	ρ-Value
BLEU	0.401
NIST	0.481
METEOR	0.513
TER	0.384
WER	0.345

Table: Interpretation of Pearson's correlation coefficient and scores for different metrics

- Highest correlation score of METEOR indicates it as the best automatic metric

Kendall's tau(τ) rank correlation[14]

$$\tau_b = \frac{n_c - n_d}{\sqrt{(n_0 - n_1)(n_0 - n_2)}}$$

where

$n_0 = n(n-1)/2$
$n =$ number of segments
$n_1 = \sum_i t_i(t_i - 1)/2$
$n_2 = \sum_j u_j(u_j - 1)/2$
$n_c =$ Number of concordant pairs
$n_d =$ Number of discordant pairs
$t_i =$ Number of tied values in the i^{th} group of ties for the first quantity
$t_j =$ Number of tied values in the j^{th} group of ties for the second quantity

Given a set of manual and automatic score pairs:
$\{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$,
any pair of scores, $(x_i, y_i), (x_j, y_j) : i \neq j$ are:
Concordant if $x_i > x_j$ and $y_i > y_j$; or if both $x_i < x_j$ and $y_i < y_j$
Discordant if $x_i < x_j$ and $y_i > y_j$; or if $x_i > x_j$ and $y_i < y_j$

Metrics	τ-Value
BLEU	0.287
NIST	0.336
METEOR	0.361
TER	0.269
WER	0.219

Table: Kendall's τ correlation scores for different metrics

- Above Score also indicate that best automatic metric for English-to-Hindi translation pair is **METEOR**
- Automatic scores has weak correlation with manual scores

Distribution: Manual Vs. Automatic

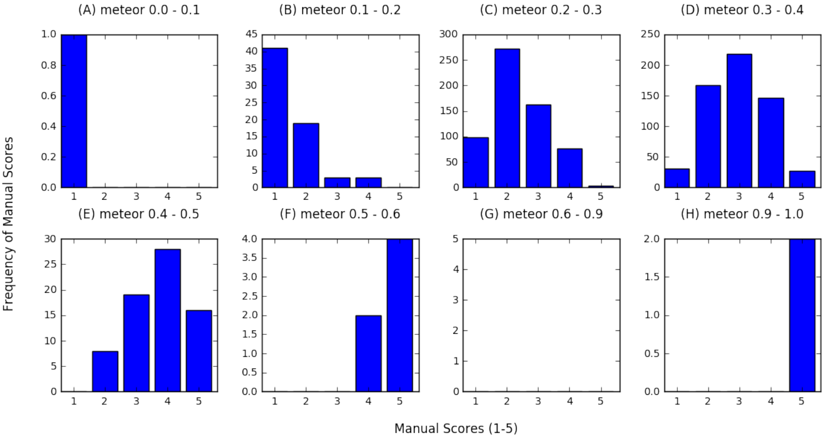


Figure: Distribution of Manual Scores for each interval of Meteor Scores

Meteor Scores	Manual scores
0.0 - 0.1	NA
0.1 - 0.2	1.48 - 1.88
0.2 - 0.3	2.52 - 2.66
0.3 - 0.4	3.11 - 3.26
0.4 - 0.5	3.73 - 4.12
0.5 - 0.6	4.56 - 5.0
0.6 - 0.9	NA
0.9 - 1.0	5.0 - 5.0

Table: 95% Confidence Interval of Manual Scores for Each interval of Meteor Scores

- Automatic scores have a weak correlation with manual scores
- METEOR correlates best with *Adequacy*
- Quality of MT can be estimated from METEOR scores in certain ranges

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Thank You !!!