### PRESENTATION

# MT Quality Evaluations: From Test Environment to Production

**ELAINEOCURRAN** Welocalize October 2015



# AGENDA

- Our MT evaluation methodologies
- Correlations between automatic scores and human evaluations
- Differences between system autoscores and PE autoscores
- MT evaluations in a production setting
- MT evaluations of post-edited files: a case study



## OUR EVALUATION METHODS

### **A TYPICAL EVALUATION PROCESS PER LOCALE AND PER ENGINE**





# OUR EVALUATION METHODS

### **AUTOMATIC SCORES GENERATED BY WESCORE**





### OUR EVALUATION METHODS **HUMAN EVALUATIONS: ADEQUACY AND FLUENCY SCORING**

S	COI	RE
	5	
	4	
	3	
	2	
	1	

#### ACCURACY

All meaning expressed in the source fragment appears in the translation fragment.

Most of the source fragment meaning is expressed in the translation fragment.

Much of the source fragment meaning is expressed in the translation fragment.

Little of the source fragment meaning is expressed in the translation fragment.

None of the meaning expressed in the source fragment is expressed in the translation fragment.

#### FLUENCY

Native language fluency. No grammar errors, good word choice and syntactic structure. No PE required.

Near native fluency. Few terminology or grammar errors which don't impact the overall understanding of the meaning. Little PE required.

Not very fluent. About half of translation contains errors and requires PE.

Little fluency. Wrong word choice, poor grammar and syntactic structure. A lot of PE required.

No fluency. Absolutely ungrammatical and for the most part doesn't make any sense. Translation has to be re-written from scratch



# OUR EVALUATION METHODS

### HUMAN EVALUATION: ERROR TYPOLOGY



# OUR EVALUATION METHODS

#### **HUMAN EVALUATION: ENGINE RANKING**

**Engine Ranked Best (out of 100 segments)** 





## LESSONS LEARNED

- We always perform autoscoring PLUS human scoring for all our MT evaluations. We have internal thresholds that qualify an engine ready for deployment and it's level of maturity.
- For bake-offs between several engines, we always include engine ranking in addition to our standard scores.
- Productivity tests are valuable during the initial phase of an MT program to build up productivity data for future reference across languages, domains and MT systems.
- Our MT program is now mature and we are able to perform most of our evaluations based on autoscoring PLUS human scoring, and by referencing the productivity data we have collected over a number of years.





# NEXT

Correlations between automatic scores and human evaluations



## CORRELATIONS

### CORRELATIONS BETWEEN AUTOMATIC SCORES AND HUMAN EVALUATIONS

Pearson's r	Variables	Variables Strength of Correlation				
0.50576955	Fluency & METEOR	Strong positive relationship	150	11		
0.50070425	Fluency & BLEU	Strong positive relationship	150	11		
0.49816365	Fluency & Recall	Strong positive relationship	150	11		
0.49724893	Fluency & NIST	Strong positive relationship	150	11		
0.49195687	Fluency & GTM	Strong positive relationship	150	11		
0.47064566	Fluency & Precision	Strong negative relationship	150	11		
0.38293518	Adequacy & NIST	Moderate negative relationship	150	11		
0.31354314	Adequacy & METEOR	Moderate negative relationship	150	11		
0.2940756	Adequacy & Recall	Weak positive relationship	150	11		
0.28586852	Adequacy & GTM	Weak positive relationship	150	11		
0.28386332	Adequacy & BLEU	Weak positive relationship	150	11		
0.26685854	Adequacy & Precision	Weak positive relationship	150	11		
-0.40270902	Adequacy & TER	Strong negative relationship	150	11		
-0.4788575	Fluency & PE Distance	Strong negative relationship	150	11		
-0.5385275	Adequacy & PE Distance	Strong negative relationship	150	11		
-0.5421933	Fluency & TER	Strong negative relationship	150	11		



## CORRELATIONS

#### THE STRONGEST CORRELATION WAS FOUND BETWEEN FLUENCY AND TER





# CORRELATIONS

### THE 2<sup>ND</sup> STRONGEST CORRELATION WAS FOUND BETWEEN ADEQUACY AND PE DISTANCE





# LESSONS LEARNED

- It seems that we cannot rely solely on autoscores as long as the correlation with human judgment is not stronger than the data suggests
- TER and PE Distance show the strongest correlation to both Fluency and Adequacy, and therefor seem closer to human judgment than the other scores.
- Fluency correlates stronger with system autoscores than Adequacy overall.
- PE Distance is the only metric that correlates stronger with Adequacy than Fluency. PE Distance is also the only character-based metric.





# NEXT

Differences between system autoscores and post-editing autoscores



### SYSTEM VS PE AUTOSCORES ON AVERAGE, THE POST-EDITING SCORE IS 15 AND 17 **POINT HIGHER FOR PE DISTANCE AND BLEU RESPECTIVELY**

Pearson's r	Variables	Strength of Correlation
0.832226688	BLEU (System) & BLEU (PE)	Very strong positive relationship
0.832218909	PE Distance (System) & PE Distance (PE)	Very strong positive relationship



Tests (N)	Locales
57	9
57	9



# SYSTEM VS PE AUTOSCORES

#### **CORRELATIONS BETWEEN SYSTEM BLEU AND POST-EDITING BLEU**







# SYSTEM VS PE AUTOSCORES

#### **CORRELATIONS BETWEEN SYSTEM PE DISTANCE AND POST-EDITING PE DISTANCE**



70%



## SYSTEM VS PE AUTOSCORES

### **REAL DATA WHERE WE COMPARE EVALUATION SCORES WITH SCORES FROM A 3-MONTH PILOT**

**PE Distance (%)** 

Pilot1 Eval1



LOOK FOR CONSISTENCY AND BEWARE OF OUTLIERS



## LESSONS LEARNED

- There is a very high correlation between the MT system autoscores generated during the evaluation phase and the autoscores generated from production using the same engines.
- However, the post-editing autoscores are considerably better than the MT system autoscores by around15%.
- We now differentiate the autoscores in our database as 'System' and 'PE'.





# NEXT

# MT evaluations in a production setting



### HOW TO MEASURE POST-EDITING EFFORT

- It is important to monitor the performance of MT and post-editors, especially during the initial launch of a new program
- The use of autoscoring to analyze post-project files is a valuable and cost-effective method to measure the post-editing effort
- They support rate negotiations and can help us to identify over- or under-editing by post-editors
- TER and PE Distance are useful metrics, with different underlying algorithms



### HOW TO MEASURE POST-EDITING EFFORT

**PE Distance -** lower is better!

- Measures the number of insertions, deletions, substitutions required to transform MT output to the required quality level
- PE Distance values are derived by comparing the post-edited segments with the corresponding machine translation segments
- In our analysis the PE distance applies the Levenshtein algorithm and is character-based. This captures morphological post-edits, such as fixing word forms.



### **HOW TO MEASURE POST-EDITING EFFORT**

**TER - lower is better!** 

- TER stands for Translation Edit Rate
- It is an error metric for machine translation that measures the number of edits required to change a system output into the postedited version
- Possible edits include the insertion, deletion, and substitution of single words as well as shifts of word sequences.
- Unlike PE Distance, TER is a word-based error metric and therefor does not capture morphological changes during post-editing.



### LOOK FOR CONSISTENCY AND BEWARE OF OUTLIERS

PE Distance (%)





### PRODUCTION SETTING LOOK FOR CONSISTENCY AND BEWARE OF OUTLIERS: POST-PROJECT AUTOSCORES INDICATE UNDEREDITING





### **TOOLS TO MEASURE POST-EDITING EFFORT**

TOOL	<b>INPUT FILES</b>	OUTPUT REPORT	PROS
iOmegaT	xliff & more	xml	Includes productivity data
MateCat	xliff	Excel	Includes productivity data as a built in feature
Okapi	xliff	html	Allows us to measure PE distance post-project
Post-Edit Compare	sdlxliff	html	Allows us to measure PE distance post-project
Qualitivity	sdlxliff	Excel	Includes productivity data
wescore	tmx	Excel	Allows us to measure PE distance post-project

#### CONS

enerated in the CAT tool during translation, requires post-editor buy-in

Generated in the CAT tool during translation, requires post-editor buy-in

Requires access to pre-and post-edited file sets

Requires access to pre-and post-edited file sets

Generated in the CAT tool during translation, requires post-editor buy-in

Proprietary tool, Requires access to pre- and postedited file sets



### MATECAT IS A FREE ONLINE CAT TOOL WITH EDITING LOG

C 🖍 🗋 www.matecat.com/support/translation-toolbox/editing-log/

The Editing Log contains statistical information about the translation.

**11601337 (43563) > en-US > fr-FR** 

< Back to Translatio

#### Job 43563 - Editing Log

Slowest 5.000 segments by time-to-edit

#### Summary

Words	Words Avg Secs per Word		% of TM	Total Time-to-edit	Avg PEE %	% of words SLOW e
877	6.1s	100%	0%	01h:25m:24s	38%	4%

#### **Editing Details**

	Secs/Word	Job ID	Segment ID	Words	Suggestion source	Match percentage	Time-to-									
$\triangle$	254.4	43563	<u>21799870</u> 18.00		Machine Translation	85%	16m:18									
	Segment	To view an article in 3	ס view an article in 3D, select it and press the <g id="185">3D View</g> button below the preview pane.													
	Suggestion	Pour voir un article en 3D, sélectionnez-le et appuyez sur la <g id="185"> Vue 3D </g> bouton ci-dessous le panneau de pré														
	Translation	Pour voir un article e	our voir un article en 3D, sélectionnez-le et appuyez sur le bouton · <g id="185">3D View</g> · sous le panneau de prévisu													
	Diff View	Pour voir un article e panneau de prévisua	n 3D, sélectionnez-le e lisation.	et appuyez sur <del>la <g id="&lt;/del"></g></del>	" <del>185"&gt; Vue 3D  bo</del>	<del>outon ci-dessous</del> le bou	ıton <g id="18</th>									

#### http://www.matecat.com/support/translation-toolbox/editing-log/

on 📘	Export All Data in CSV	/
in too	% of words in too	
dits	FAST edits	
	0%	
edit	PE Effort	
ls	24%	
isualisatio	on.	
alisation.		
5">3D Vi	iew sous le	

welocalize of things differently

### **USE POST-EDIT COMPARE TO ANALYSE SDLXLIFF FILES**



http://www.translationzone.com/openexchange/app/post-editcompare-495.html

_				
s		$\square$		
s	Characters	Percent	Tags	Total
6	22581	7.50%	0	0 ()
1	12352	7.71%	54	0 ()
3	36004	22.71%	276	0 ()
7	38309	23.57%	428	0 ()
8	52569	32.23%	1286	0 ()
6	11008	6.29%	582	0 ()
		$\setminus$ /		
1	172823	100%	2626	0 ()
		Post-Edit (W	ords)	
	100%	100%	99-9	a 1/3 🕨
1	99-95%			
(	94-85%			
	84-75%			
	74-50%	32.2%		
	New	52.270		22.7%
1				
	·			



### **OKAPI FRAMEWORK TRANSLATION COMPARISON STEP**

#### Summary

Repartition for Trans1 to Trans2:

Scores		ED-S	cores		FM-Scores				
scores	Segments	%	Words	%	Segments	%	Words	%	
100	139	3	1414	3	176	4	1802	4	
90 - 99	350	8	3954	8	346	8	3864	8	
80 - 89	862	20	9850	20	674	16	7659	15	
70 - 79	971	22	11137	23	804	19	9191	19	
60 - 69	1078	25	12423	25	805	19	9332	19	
50 - 69	598	14	6794	14	655	15	7500	15	
40 - 59	197	5	2215	4	392	9	4479	9	
30 - 39	33	1	359	1	240	6	2775	6	
20 - 29	2	0	22	0	102	2	1159	2	
10 - 19	1	0	4	0	36	1	398	1	
0 - 9	104	2	1258	3	105	2	1271	3	
Total	4335	100%	49430	100%	4335	100%	49430	100%	

Total Number of Segments:	4335
Total Number of Words:	49430
Average word count per segment:	11.40
Average ED-Score (by segment):	Trans1 to Trans2 = 69.95
Average FM-Score (by segment):	Trans1 to Trans2 = $65.48$
Average ED-Score (by word):	Trans1 to Trans2 = $69.76$
Average FM-Score (by word):	Trans1 to Trans2 = 65.18
Edit Effort Score:	32.53

http://www.opentag.com/okapi/wiki/index.php?title=Translation\_Comparison\_Step



### **QUALITIVITY PLUGIN FOR SDL TRADOS STUDIO**

Activit	ty Documents																		•	<b>,</b>
	Document Overview	🛐 Doc	ument Red	ords	火 ро	cument Reports														
	Document: SamplePhoto	Printer.	doc.sdlxlif	f										Total E	Elapsed Time:	00:00:42 (h	ours: 0.012) D	ocument A	tivities: 1	
	Translation Modifications	5	Segments	;	Words	Characters	Tags	Post-Edit M	odifications A	Analysis						Comfirm	ation Statistics	(segments)		
		Total	Modified	%				Туре	Segments	Words	Characters	Percent	Tags	Price	Total	Confirm	ation Level	Original	Updated	
I	Perfect Match	0	0	0%	0	0	0	100%	0	0	0	0%	0	0.002	0.00 (EUR)	Not Tran	slated	8	8	0'
	Context Match	0	0	0%	0	0	0	95% - 99%	0	0	0	0%	0	0.024	0.00 (EUR)	Draft		11	11	0'
1	Exact Match	0	0	0%	0	0	0	85% - 94%	0	0	0	0%	0	0.078	0.00 (EUR)	Translat	ed	0	0	0'
	Automated Translation	11	3	27%	41	219	1	75% - 84%	1	18	90	43.90%	0	0.09	1.62 (EUR)	Translat	ed Rejected	0	0	0'
I	Fuzzy Match	0	0	0%	0	0	0	50% - 74%	2	23	129	56.10%	1	0.12	2.76 (EUR)	Translat	ed Approved	0	0	0'
1	New	8	0	0%	0	0	0	New	0	0	0	0%	0	0.12	0.00 (EUR)	Sign-off	Rejected	0	0	0'
1	Sub-Total				41	219	1	-								Signed-	off	0	0	0'
	Total	19	3	16%	41	219	1	Total	3	41	219	100%	1		4.38 (EUR)	Total			0	
D	ocument Name		Source	Та	rget i	Activity Type	Trans	lation Modifica	tions Stat	tus Chan	iges Quality	Metrics	Comm	ents El	lapsed Time	Opened	CI	osed		
s	amplePhotoPrinter.doc.s	dlxliff	en-	us 📕	it-IT	Translation	3		0		0		0	0(	0:00:42	6/15/2015 5	:13:56 PM 6/1	15/2015 5:1	4:39 PM	
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http://www.translationzone.com/openexchange/app/qualitivity-788.html



## LESSONS LEARNED

- The use of autoscoring to analyze post-project files is a valuable and costeffective method to measure the post-editing effort.
- A productivity test requires upfront organization and buy-in from translators.
- It is important to find a tool that works with the given file format and workflow.
- Access to pre- and post-edit versions of projects is required. This is a challenge on some accounts.
- Identification and separation of MT segments from fuzzy segments may be required for some tools.
- Look for consistency across languages and resources. Unusually high or low scores can be a sign of over-editing or under-editing.



# NEXT

#### MT evaluations of postedited files: a case study



## CASE STUDY

### **TEST PILOT FOR LIGHT AND FULL POST-EDITING**

- Languages: Chinese (Simplified) and Japanese
- The resources are regular translators for this client
- In order to have comparable data, the same resource performed both light and full post-editing tasks of 438 segments





## CASE STUDY: HUMAN EVALS

### **ADEQUACY AND FLUENCY SCORES**







## CASE STUDY: AUTOSCORES

### AUTOSCORES FOR LIGHT AND FULL POST-EDITING



—ja-JP Full PE

-zh-CN Full PE

—ja-JP Light PE

-zh-CN Light PE



TER

# CASE STUDY: PRODUCTIVITY

### PRODUCTIVITY FOR LIGHT AND FULL POST-EDITING



# CASE STUDY: LESSONS

### **LESSONS LEARNED**

- Using autoscores on post-edited translations can indicate the level of post-editing effort involved for a specific content and MT engine
- The autoscores also illustrate the difference in effort between Light and Full Post-editing, approximately 20 point delta for BLEU and 15 point delta for TER
- The autoscores confirm that the resources have indeed managed to perform two distinct post-editing levels



