



# Overview of the IWSLT 2009 Evaluation Campaign

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# Outline of Talk

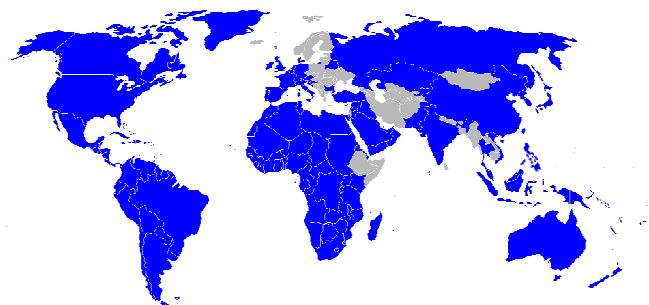
## 1. Evaluation Campaign:

- Participants
- What's New?
- Language Resources
- Challenge Task 2009
- Evaluation Specifications

## 2. Evaluation Results:

- Automatic Evaluation
- Subjective Evaluation
- Correlation between Evaluation Metrics
- Innovative Ideas explored by Participants

# IWSLT 2009 Participants



ES: 2



SG: 2



FR: 3



US: 2



IE: 1



TR: 2



IT: 1



ZH: 2



JP: 3

**Teams: 18**  
**Engines: 35**

Research Group		System
TR	AppTek, Inc.	apptek *
ES	Barcelona Media	bmrc *
IE	Dublin City University	dcu
IT	Fondazione Bruno Kessler	fbk
FR	University of Caen Basse-Normandie	greyc
SG	Insititute for Infocomm Research	i2r
ZH	Chinese Academy of Science, ICT	ict
FR	University J. Fourier, LIG	lig
FR	University of Le Mans, LIUM	lium
US	MIT Lincoln Lab / Air Force Research Lab	mit
JP	NICT	nict
ZH	Chinese Academy of Science, NLPR	nlpr
SG	National University of Singapore	nus *
JP	University of Tokyo	tokyo *
JP	Tottori University	tottori
TR	TÜBİTAK-UEKAE	tubitak
ES	University Politecnica de Valencia	upv *
US	University of Washington	uw

\* first-time participation

# What's New?

- Challenge Task

- translation of **cross-lingual human-mediated dialogs** in a travel situation (SLDB data, **Chinese↔English**)
- **context annotations** (dialog, speaker-role)
- ASR output (lattices, N/1-BEST lists)

- BTEC Task

- **only TEXT input** for all classic BTEC tasks (**Arabic/Chinese→English**)
- **new input languages:** **Turkish →English**

- Single Data Track

- **usage of supplied language resources only**

- Extended Training/Run Submission Period

- 2 month for training, 2 weeks for submitting runs

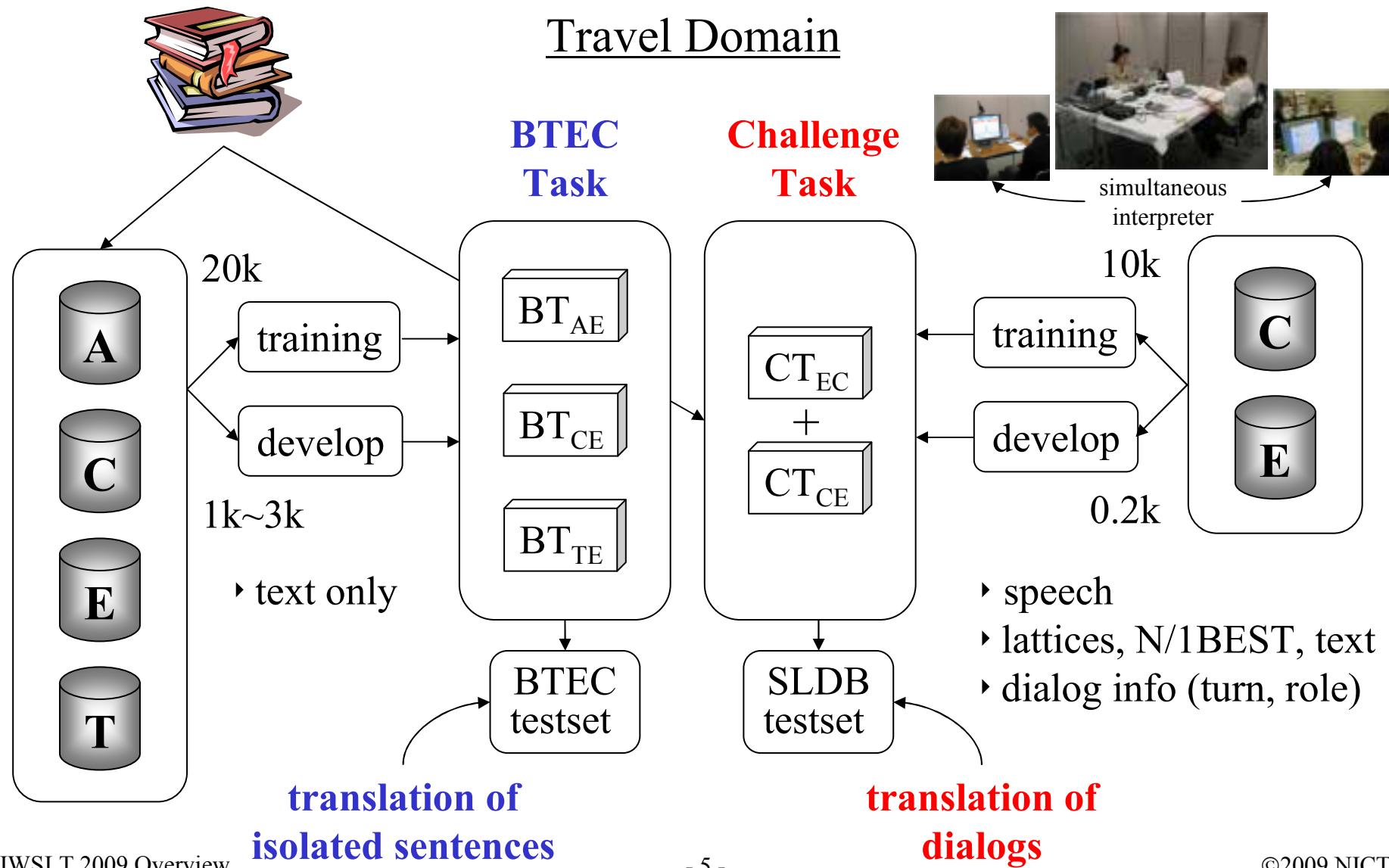
- Evaluation

- investigate **effects of dialog information on MT quality**

# Language Resources

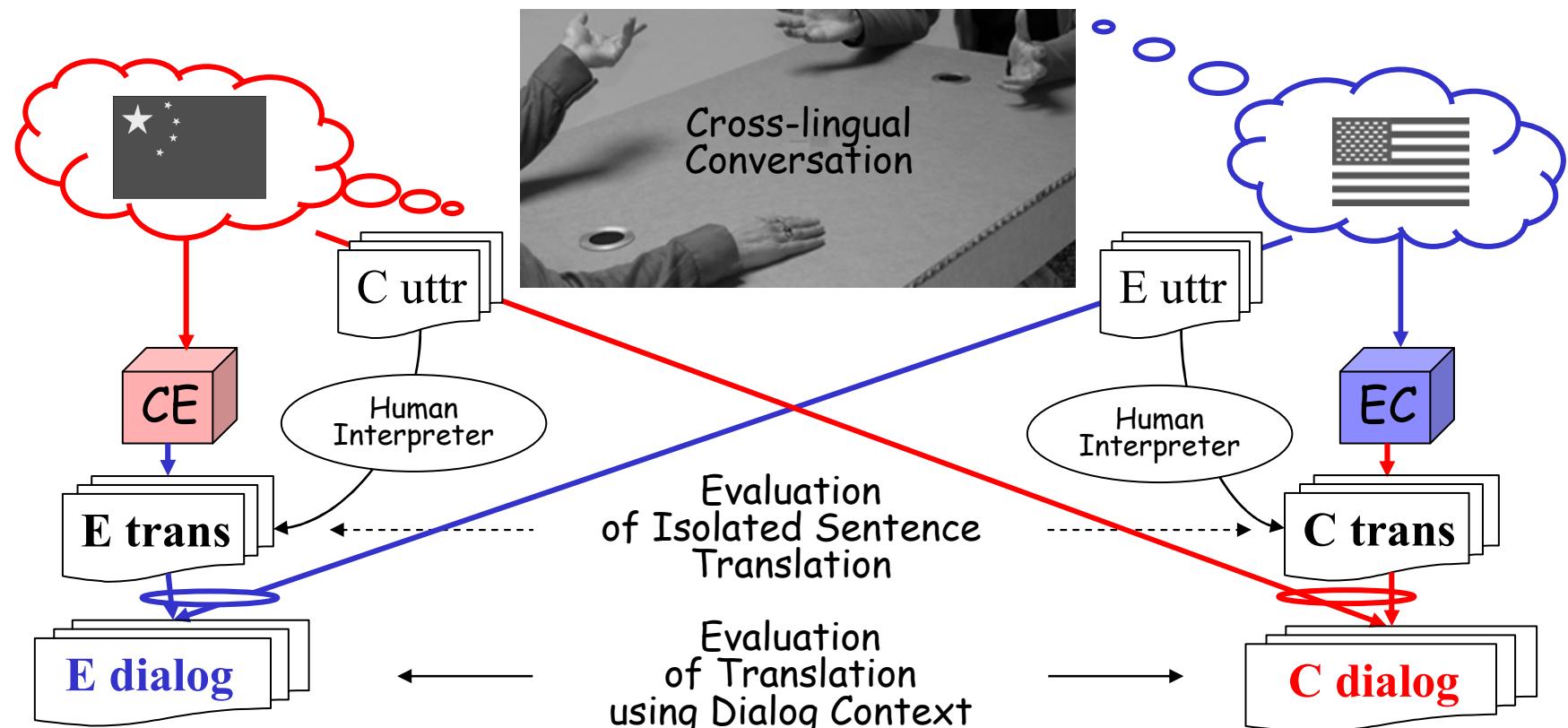
**BTEC**  
(Basic Travel Expression Corpus)

**SLDB**  
(Spoken Language Database)



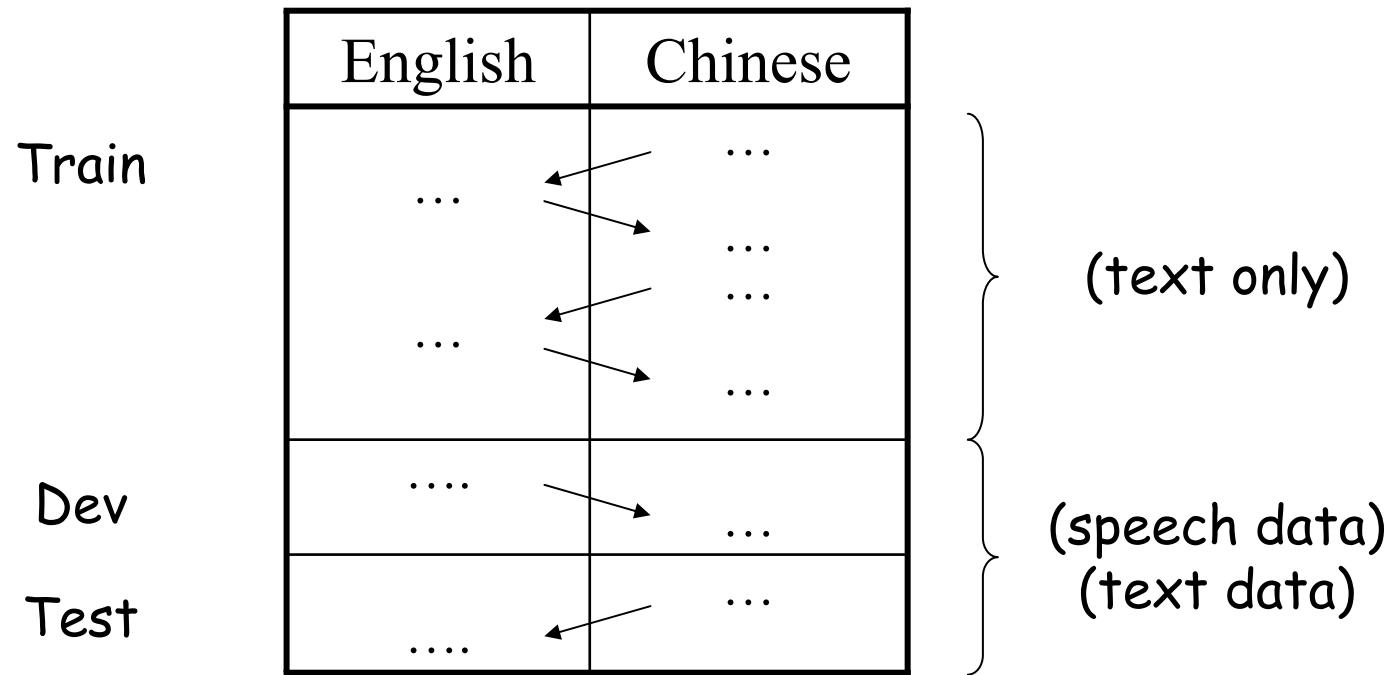
# Challenge Task

- translation of human-mediated **cross-lingual conversations**
  - **task-oriented dialogs (role-play) in a travel situation**
  - *translation directions: C → E, E → C*



# Challenge Task

- SLDB dialog data:



(train) 400 dialogs, ~10,000 sen  
 (dev) 10 dialogs, ~400 sen  
 (test) 27 dialogs, ~800 sen

# Challenge Task

- Dialog Example:

(speaker) interjections uttered  
(interpreter) *interjections skipped*

Agent:	Okay, no problem. And, will you be paying by cash or charge, sir? (interpreter) 好的。您用现金，还是用信用卡？
Customer:	嗯 我要用信用卡。 (interpreter) By <u>credit card</u> .
Agent:	Okay. Could I have your <u>number</u> in that case, please? (interpreter) 好的。那么，请告诉我 <u>信用卡号码</u> 。
Customer:	维萨卡。 (interpreter) It's a VISA card.
Customer:	号码, 四九八零零四五九。 (interpreter) The number is four nine, eight, o, o four, five nine.
Customer:	九一九九五三一三。 (interpreter) Nine one, nine nine, five three, one three.
Agent:	Okay. Thank you. Uhmm and when does it expire? (interpreter) 知道了。信用卡什么时候到期？
Customer:	嗯 明年四月到期。 (interpreter) It <b>expires</b> in April, next year.

(speaker) “ends at”  
(interpreter) *context-specific word selection*

# Statistics of Evaluation Data Sets

Track	Lang	Sen	Length	Word	Voc	Ref
CT <sub>EC</sub>	E	393	11.0	4,329	570	—
	C		10.5	16,558	872	4
CT <sub>CE</sub>	C	405	11.3	4,562	653	—
	E		11.5	18,594	764	4
BT <sub>CE</sub>	C	469	5.5	1,808	877	—
	E		7.1	23,149	1,526	7

- BTEC sentences are shorter than CHALLENGE utterances
- CHALLENGE vocabulary is smaller than the BTEC vocabulary

# Translation Task Complexity

Set	Lang	Entropy	Words	Total Entropy	Track
testset	C	6.18	4,142	25,580	CT <sub>EC</sub>
	E	5.43	4,501	24,446	CT <sub>CE</sub>
		5.80	2,844	15,063	BT <sub>CE</sub> BT <sub>AE</sub> BT <sub>TE</sub>

- larger total entropy for CHALLENGE references  
 → CHALLENGE task is supposed to be **more difficult than BTEC task**

# Recognition Accuracy

Set	Lang	Word (%) Lattice 1BEST	Sentence(%) Lattice 1BEST	Track
testset	C	91.82	75.81	57.64 29.32 $CT_{CE}$
	E	89.58	82.20	50.13 37.15 $CT_{EC}$

- **large difference** in word recognition accuracy **for lattice vs. 1BEST** for Chinese utterances, but smaller for English
  - **even larger difference** in recognition accuracies **on the sentence-level** for both, Chinese and English
- **decoding of lattices** (or at least NBEST) has potential to **produce translations of better quality**

# Evaluation Specifications

**Automatic Evaluation:** → all primary run submissions

- **case-sensitive, with punctuation marks** (*case+punc*)
- case-insensitive, without punctuation marks (*no\_case+no\_punc*)
- 7 standard metrics:

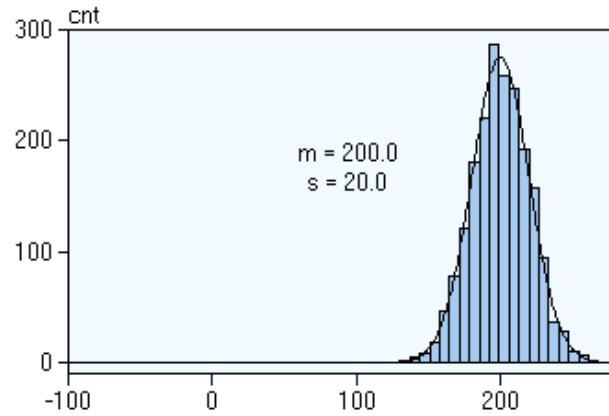
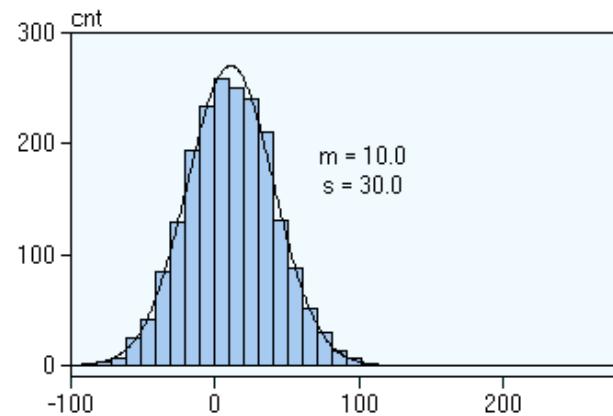
+ BLEU	+ NIST	+ WER	+TER
+ METEOR (f1)	+ GTM	+ PER	

# Evaluation Specifications

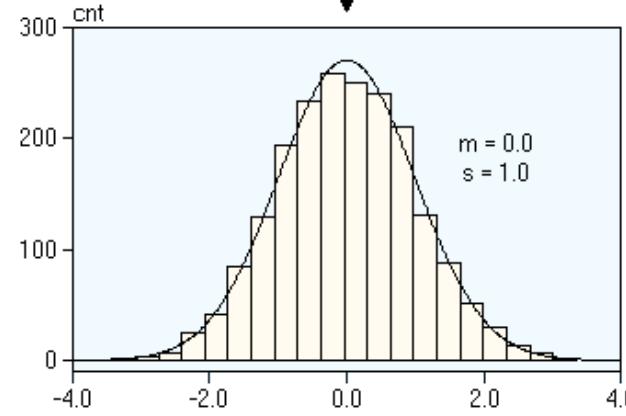
## Significance Test:

- (1) perform a **random sampling with replacement** from the evaluation testset
- (2) **calculate** respective evaluation metric scores for each MT engine and the **differences between the two MT engine scores**
- (3) **repeat sampling/scoring steps** iteratively (2000 iterations)
- (4) **apply Student's t-test at a significant level of 95%** to test whether score differences are significant

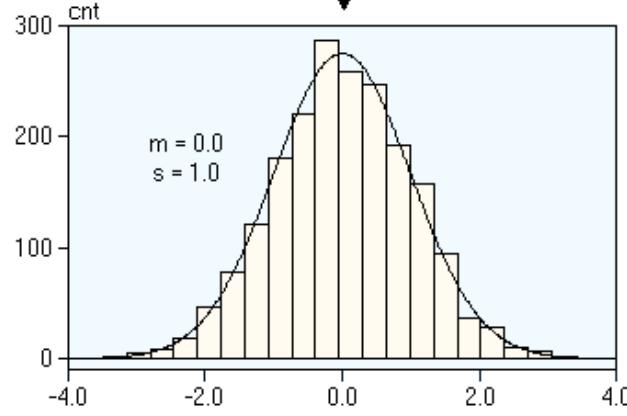
# Metric Score Combination



Standardisation



comparable distributions  
( $m = 0.0, s = 1.0$ )



# Metric Score Combination

## Z-Transform:

- standardize a distribution so that:
  - + it has a **zero mean**              ( $\mu = 0$ )
  - + it has **unit variance**              ( $\sigma^2 = 1$ )

$$z_i = \frac{(x_i - \mu)}{\sigma}$$

$\{x_i\}$  : a set of  $n$  sample values from score distribution

$\mu$  : mean of sample values

$\sigma$  : standard deviation

$\sigma^2$  : variance of the distribution

# Evaluation Specifications

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- 7 standard metrics:

+ BLEU	+ NIST	+ WER	+ TER
+ METEOR (f1)	+ GTM	+ PER	
- combine multiple metric scores (z-avg):
  - + normalize single-metric scores so that score distribution has a zero mean and unit variance → *z-score*
  - + for each MT system, calculate **z-avg** as the average of all obtained metric *z-scores*
- for each translation task, **order MT systems according to z-avg**

# Evaluation Specifications

## Human Assessment:

- **Ranking** (grades 4 – 0) → all primary run submissions
  - + rank each whole sentence translation from Best to Worst relative to the other choices (ties are allowed)
- **Fluency/Adequacy** (grades 4 – 0) → top-ranked MT engine
  - + *Fluency* indicates how the translation sounds to a native speaker
  - + *Adequacy* judges how much reference information is expressed in the translation
- **Dialog Adequacy** (grades 4 – 0) → top-ranked MT engine
  - + an adequacy evaluation that takes into account the context of the respective dialog
  - + omitted information in translation that is understood in the dialog context should not result in a lower *dialog adequacy* grade

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# Data Track Participation

Task	Translation Direction	Team	Run	
			primary	contrastive
Challenge	English-Chinese	CT <sub>EC</sub>	7	6 14
	Chinese-English	CT <sub>CE</sub>	7	6 12
BTEC	Arabic-English	BT <sub>AE</sub>	9	9 9
	Chinese-English	BT <sub>CE</sub>	12	12 19
	Turkish-English	BT <sub>TE</sub>	7	7 15
Total			18	40 69

# Automatic Evaluation

**z-avg** (BLEU, METEOR, 1-WER, 1-PER, 1-TER, GTM, NIST)

CT <sub>EC</sub>	
<b>nlpr_ASR.5</b>	<b>1.364</b>
nict_ASR.1	1.017
fbk_ASR.1	0.881
dcu_ASR.1	0.659
ict_ASR.20	0.194
tottori_ASR.1	-1.544

nlpr_CRR	
fbk_CRR	1.026
ict_CRR	0.748
nict_CRR	0.613
dcu_CRR	0.570
tottori_CRR	-1.634

*input*

ASR



lattice, N/1BEST

CT<sub>CE</sub>

**nlpr\_ASR.5**    **2.063**

dcu\_ASR.1    0.704

fbk\_ASR.1    0.530

ict\_ASR.20    0.405

nict\_ASR.1    -0.378

tottori\_ASR.1    -0.751

CRR



correct recognition  
result

**nlpr\_CRR**    **1.851**

dcu\_CRR    1.214

fbk\_CRR    0.398

ict\_CRR    0.326

nict\_CRR    -0.424

tottori\_CRR    -0.793

# Automatic Evaluation

**z-avg** (BLEU, METEOR, 1-WER, 1-PER, 1-TER, GTM, NIST)

BT <sub>AE</sub>	
<b>mit+tub</b>	<b>1.504</b>
mit	1.432
fbk	0.940
tubitak	0.504
lium	0.465
bmrc	0.456
lig	0.325
uw	0.137
greyc	-1.941

BT <sub>CE</sub>	
<b>nlpr</b>	<b>2.178</b>
nus	1.344
i2r	1.250
uw	0.786
dcu	0.545
bmrc	0.489
lium	0.323
upv	0.068
tokyo	0.022
ict	-0.011
tottori	-0.405
greyc	-1.444

BT <sub>TE</sub>	
<b>mit+tub</b>	<b>1.304</b>
mit	1.216
tubitak	1.043
fbk	0.912
dcu	0.502
apptek	-0.536
greyc	-1.441

# Ranking

**CT<sub>EC</sub>**

<b>nlpr_ASR.5</b>	<b>3.48</b>
nict_ASR.1	3.02
<b>dcu_ASR.1</b>	2.80
<b>fbk_ASR.1</b>	2.79
ict_ASR.20	2.63
tottori_ASR.1	2.18

<b>nlpr_CRR</b>	<b>3.84</b>
<b>ict_CRR</b>	3.67
<b>nict_CRR</b>	3.42
<b>fbk_CRR</b>	3.32
dcu_CRR	3.31
tottori_CRR	2.58

**NormRank**



normalized ranks  
on a per-judge basis  
[Blatz et.al. 2003]

**CT<sub>CE</sub>**

<b>nlpr_ASR.5</b>	<b>3.52</b>
<b>ict_ASR.1</b>	2.90
<b>dcu_ASR.1</b>	2.84
<b>nict_ASR.20</b>	2.80
<b>fbk_ASR.1</b>	2.75
tottori_ASR.1	2.60

<b>nlpr_CRR</b>	<b>3.67</b>
<b>dcu_CRR</b>	3.32
<b>fbk_CRR</b>	3.26
<b>ict_CRR</b>	3.20
<b>nict_CRR</b>	3.11
tottori_CRR	2.83

MT systems marked  
in **blue** were ranked  
differently by  
automatic metrics

# Ranking

NormRank 0  4  
bad good

BT <sub>AE</sub>	
mit	<b>3.29</b>
mit+tub	3.28
fbk	3.03
tubitak	3.03
lium	3.01
bmrc	2.95
lig	2.87
uw	2.86
greyc	2.38

BT <sub>CE</sub>	
nlpr	<b>3.55</b>
nus	3.24
i2r	3.17
uw	3.12
dcu	3.01
bmrc	2.99
lium	2.95
upv	2.91
tokyo	2.87
ict	2.84
tottori	2.78
greyc	2.63

BT <sub>TE</sub>	
mit+tub	<b>3.26</b>
mit	3.25
tubitak	3.23
fbk	3.13
dcu	2.92
apptek	2.74
greyc	2.39

# Best Rank Difference

- use the MT system with highest ranking score as a point-of-reference
- rank systems according to difference in rank against the best system1
  - metric: gain ( $\frac{better - worse}{graded}$ ) of the top MT towards any other system in %



CT <sub>EC</sub>	<i>better</i>	<i>same</i>	<i>worse</i>	
<b>nlp<sub>r</sub>_ASR.5</b>	—	—	—	
nict_ASR.1	<b>29.85</b>	50.24	29.37	20.39
fbk_ASR.1	<b>36.72</b>	53.09	30.54	16.37
dcu_ASR.1	<b>36.96</b>	51.70	33.56	14.74
ict_ASR.20	<b>48.64</b>	61.26	26.12	12.62
tottori_ASR.1	<b>61.65</b>	70.42	20.81	8.77

# Correlation between Automatic Evaluation and Ranking

◦ Spearman's rank correlation coefficient  $\rho \in \{-1.0, 1.0\}$

task	metric	z-avg
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<b>CT<sub>EC</sub></b> (ASR:6)	NormRank	<b>0.9429</b>
	BestRankDiff	0.8857

<b>CT<sub>EC</sub></b> (CRR:6)	NormRank	<b>0.8286</b>
	BestRankDiff	0.7143

<b>CT<sub>CE</sub></b> (ASR:6)	NormRank	<b>0.7143</b>
	BestRankDiff	0.6000

<b>CT<sub>CE</sub></b> (CRR:6)	NormRank	<b>0.7143</b>
	BestRankDiff	0.6000

task	metric	z-avg
------	--------	-------

<b>BT<sub>CE</sub></b> (12)	NormRank	<b>-0.3846</b>
	BestRankDiff	0.2098

<b>BT<sub>AE</sub></b> (9)	NormRank	0.0333
	BestRankDiff	<b>0.1667</b>

<b>BT<sub>TE</sub></b> (7)	NormRank	<b>0.8571</b>
	BestRankDiff	-0.6071

# Correlation between Automatic Evaluation and Ranking

- combination of all investigated automatic metrics optimal?

task	NormRank	BestRankDiff
<b>CT<sub>EC</sub><sup>ASR</sup> (6)</b>	(all)	TER
<b>CT<sub>EC</sub><sup>CRR</sup> (6)</b>	f1+TER	TER
<b>CT<sub>CE</sub><sup>ASR</sup> (6)</b>	METEOR	METEOR
<b>CT<sub>CE</sub><sup>CRR</sup> (6)</b>	(all)	GTM
<b>BT<sub>CE</sub> (12)</b>	BLEU	TER
<b>BT<sub>AE</sub> (9)</b>	METEOR	PER
<b>BT<sub>TE</sub> (7)</b>	NIST	TER

# Correlation between Automatic Evaluation and Ranking

- effects of combination of multiple metrics:
    - better correlation for CT using *NormRank*
    - single metrics perform best for *BestRankDiff*
    - METEOR and TER work best for most translation tasks
    - BLEU best for BT<sub>CE</sub>, but low correlation for all other tasks
  - correlation depends on:
    - selected evaluation metrics (subjective, automatic)
    - number of MT systems to be ranked
    - translation quality of respective MT system outputs
- **simply averaging metric scores might not be the best solution**  
to combine multiple automatic evaluation metrics

# Fluency/Adequacy/Dialog

median grade of 3 human grades

## fluency

4	Flawless English
3	Good English
2	Non-native English
1	Disfluent English
0	Incomprehensible



## dialog / adequacy

4	All Information
3	Most Information
2	Much Information
1	Little Information
0	None

CT <sub>EC</sub>	CT <sub>CE</sub>	BT <sub>CE</sub>	BT <sub>AE</sub>	BT <sub>TE</sub>
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fluency	ASR: 2.35 CRR: 2.60	ASR: 2.37 CRR: 2.53	2.78	2.70	2.90
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# Fluency/Adequacy/Dialog

- **translation quality of translation tasks:**
    - fluency :  $BT_{TE} > BT_{CE} > BT_{AE} > CT_{EC} > CT_{CE}$
    - adequacy:  $BT_{TE} > BT_{CE} > CT_{CE} > CT_{EC} > BT_{AE}$
    - dialog adequacy:  $CT_{CE} > CT_{EC}$
  - **effects of dialog information on translation quality:**
    - $CT_{CE} / CT_{EC}$  : dialog adequacy  $>$  adequacy
    - larger difference for  $CT_{CE}$
- **dialog context helps** humans to understand MT outputs
- **sentence-by-sentence evaluation not sufficient** for spoken language translation technologies
- **develop new MT algorithm and evaluation metrics** capable of taking into account information beyond the current sentence

# Innovative Ideas Explored by Participants

- morphological **preprocessing** techniques
- **statistical modeling techniques** integrating syntactic and source language information
- cross-domain **model adaptation**
- new **parameter optimization** techniques
- **lattice decoding**
- semi-supervised **reranking methods** of NBEST lists
- improved **system combinations** using hybrid MT engines

# Acknowledgements

- *data preparation*
  - NICT team
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  - AppTek (English)
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  - NICT (English, Chinese)
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  - NICT: Tatsufumi Shimizu
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  - FBK team
- *local organization*
  - NICT team

Thank you!