March **2018**

Neural Won: Now What? Alex Yanishevsky Senior Manager MT and NLP Deployments





Our History

1997.	2000.	2005.	2006.	2007.	2008.	
Company Started	Expanded Market into Germany (Acquisition)	Established Headquarte (Acquisition)	European rs in Dublin	Opened APAC Services in Jinan and Beijing, China (Acquisitions)	US Acquisitions Including Global Sight Technology, Leading Open Source Training Management System	Added to APAC Presence with Tokyo Office (Acquisition)
2010.	2012.	2014.	2015.	2016.		
Major Expansion in Europe with UK Acquisition of Lloyd International	Added Legal Services with Market Leader Par IP Translations (Acquisition)	Acquirec k Solutions Acquirec Associati	l CD Language in Houston, TX l Agostini in Milan, Italy	Significant Investment from Norwest Equity Partners Acquired Adapt Worldwide (Traffic Optimiser) in London, United Kingdom	Nova Language Services Acquisition Expands Regulated Industry Solutions in Life Science (Acquisition) Global Language Solutions (GL	s S)
				11 th Year on Inc. 5000 Fastest Growing Private Companies	Acquisition Strengthens Life Sciences Market Leadership (Acquisition)	







• Did NMT really win?

• Migration path

- Build or buy?
- · Infrastructure and Cost
- TMS and Connectors
- Additional Use Cases CMS, applications using MT such as chat, KB, forums
- Training and Maintenance
- Supply Chain
- Case studies
- What else can we do with neural technology?



Proceedings of AMTA 2018, vol. 2: MT Users' Track







Generally, yes, and the future lies in NMT, but...

- Locale variants such as ES-ES>ES-MX: consider transformation tables or Apertium (RBMT)
- Related language pairs such as ES-ES>PT-PT: consider Apertium (RBMT) or SMT
- - Rare, long-tail language translation directions: consider SMT
- In some cases, well trained SMT engine in Romance languages
 - can be preferred to NMT
 - In some cases, SMT better at short sentences



		Light Marketing				Technical Documentation				
Locale	Evaluation	Generic NMT1	Generic NMT2	Customized SMT	Diff Best NMT & SMT	Generic NMT1	Generic NMT2	Customized SMT	Diff Best NMT & SMT	
	Ranking	\checkmark	2	3	6.02 pp	2	\checkmark	3	7.38 pp	
	Accuracy			\checkmark	0.06		\checkmark		0.08	
de-DE	Fluency		\checkmark		0.07		\checkmark		0.45	
	Edit Distance	2	3	\checkmark	3.32 pp	\checkmark	3	2	1.12 pp	
	Edit Distance (PE)	2		\checkmark	1.55 pp					
6.50	Ranking	\checkmark	3	2	1.97 pp	\checkmark	2	3	7.29 pp	
П-РК	Edit Distance	2	3	\checkmark	2.02 pp	2	3	\checkmark	0.62 pp	
	Ranking	\checkmark	2	3	12.96 pp	\checkmark	2	3	10.51 pp	
	Accuracy		\checkmark		0.32		\checkmark		0.76	
ja-JP	Fluency		\checkmark		0.2		\checkmark		0.49	
	Edit Distance	\checkmark	3	2	8.17 pp	\checkmark	3	2	5.79 pp	
	Edit Distance (PE)	\checkmark		2	21.07 pp					
	Ranking	\checkmark	3	2	4.59 pp	\checkmark	2	3	6.65 pp	
	Accuracy		\checkmark		0.09		\checkmark		0.26	
pt-BR	Fluency		\checkmark		0.45		\checkmark		0.28	
	Edit Distance	2	3	\checkmark	1.68 pp	\checkmark	3	2	0.28 pp	
	Edit Distance (PE)	2		\checkmark	3.62 pp					
zh CN	Ranking	\checkmark	2	3	10.57 pp	\checkmark	2	3	10.40 pp	
211-CIN	Edit Distance	\checkmark	3	2	5.87 pp	\checkmark	3	2	3.12 pp	
ru PH	Ranking	\checkmark	2	3	5.95 pp					
Tu-KU	Edit Distance	2	3	\checkmark	1.58 pp					



SMT better for DE for accuracy and edit

SMT better for PTBR for edit distance



 \checkmark

[//

SMT better for RU for edit distance



Proceedings of AMTA 2018, vol. 2: MT Users' Track

Engine	Content	BLEU	NIST	METEOR	GTM	PE Dist	TER	Precision	Recall	Length (Hyp./Ref.)	Segs.	Words	PE Diff	Ranking 1	Ranking 2
		64.10	10.33	73.72	80.11	37.05%	30.93	0.82	0.79	0.96	2460	33322			
NMT	Test set												17.11%		
		60.22	9.75	71.64	78.96	54.16%	36.61	0.79	0.79	0.99	2500	33863			
MS Hub	Test set														
		63.07	8.00	73.28	77.57	50.44%	38.84	0.76	0.79	1.03	513	3852			
NMT	Aug-projects												-5.77%		
		72.38	9.34	81.98	86.89	44.67%	23.41	0.88	0.86	0.97	559	4201			
MS Hub	Aug-projects														
		54.90	7.91	66.81	72.63	59.63%	45.65	0.71	0.74	1.04	940	7265			
NMT	Oct-projects												-8.85%	43%	379
		60.96	8.84	72.95	79.79	50.78%	34.49	0.80	0.80	1.00	1057	8395			
MS Hub	Oct-projects													33%	269

The NMT engines scores better in human ranking NMT engine has a lot of omissions, duplications and unusual mistranslations

Results for auto-scoring are mixed



Proceedings of AMTA 2018, vol. 2: MT Users' Track



Now What?



PAIN POINTS Raw MT, PE, both



NUMBER OF ENGINES

How many domains and engines do you have and for how many languages?



STRATEGY

What is your migration path and strategy?





Migration Path



Migration Path



BUILD OR BUY?

TMS AND CONNECTORS

ADDITIONAL USE CASES: CMS, CHAT, KB, FORUMS

TRAINING AND MAINTENANCE

SUPPLY CHAIN

CASE STUDIES



Build or Buy /1





Build or Buy /2



BUILD BUY Modern MT 0 Google, Amazon, Bing – 0 Open NMT 0 not customizable **Tensor Flow** 0 MS Hub SMT, Globalese, 0 Nematus 0 Kantan, Omniscien, SDL, Marian 0 Systran, Iconic, etc. -• Moses customizable **BUILD** BUY Limited baseline Robust or limited 0 0 baseline based on Difficult to enforce 0 provider terminology Generally difficult to 0 enforce terminology, but

based on provider

|--|



 BUY Less options to control Very good documentation and code samples
BUY
 \$10-20 for 1 million characters – not customizable and MS Hub SMT Several hundred to several thousand per engine – customizable

TMS and CAT Tool Considerations

 $(\checkmark$



Availability and additional cost of connectors depends on TMS or CAT tool Tag handling

- Pre and post processing scripts
- Tags as sentence breakers
- Capabilities for providing feedback
- Interacting with Adaptive MT

Ideally, the TMS has several MT connectors so you can pick and choose and migrate when results are conclusive and/or run several MT providers in parallel.



Additional Use Cases of MT



- KB
- Forums
- Chat
- Any other applications



6 points of MT integration!



Training and Maintenance /1



Initial training Computational costs of building NMT vs SMT are higher

Maintenance

Computational cost of enforcing specific patterns from linguistic feedback is higher; it's not a matter of modifying phrase tables or language models as with SMT or rules/dictionaries with RBMT.



Training and Maintenance /2



- Data availability
 - ✓ Some NMT systems with restricted options require a lot more training data than comparable SMT or RBMT systems
 - 5-7 million TUs (sometimes 10-11 million) overall to match the quality of an SMT engine in MS Hub with 500-600K TUs and MS Models
 - Client data ranged from 50K to 700K TUs
 - Possible to train decent engine with 1-2 million TUs in a different framework with more options available



Training and Maintenance /3



Data Quality Bad for both

Bad for both

- Uneven or misaligned TUs
- Wrong target language
- Poor, unreliable or inconsistent translations
- Really long segments (NMT attention mechanism keeps track for only so long due to vanishing gradients, SMT – can't focus on long term dependencies, e.g. English with relative clauses)

Bad for NMT only

- Short segments (1-3 words)
- High ratios of DNT if you do not have method to enforce dictionary



Training the Supply Chain

\oslash	
\oslash	

NMT output is remarkably more fluent.

However, this fluency does not guarantee accuracy. The cognitive load can be higher for a post-editor to review the source and suggested target.



OOVs and DNT mistranslations

59805384 Giochi olimpici invernali di PyeongChang. 59805384

Source	Hypothosis	Reference
6 Div(Low)	6、、	6 分割(低)

Source	Hypothesis	Reference
a04JwiqW9El4hce/Z3+nOHOckWJ0VSCFoqox1FVpYW4fXS ylyMz/vYTAWrnj493YIY	SeHfuQ0ktVn X/Z3+Delete/bbr	a04JwiqW9El4hce/Z3+nOHOckWJ0VSCFoqox1FVpYW4fXSeHfuQ0kt VnylyMz/vYTAWrnj493YIY
Examples: file:///remote/file/system/mount/point, \\\\sents://server:/path	erver\\path or 示例:、或更高版本	示例: file:///remote/file/system/mount/point、\\\\server\\path 或 nfs://server:/path
Source	Hypothosis	Reference
<proxyaddress:port></proxyaddress:port>	<>	<pre><pre>cyproxyAddress:port></pre></pre>
GuestRpc:	:	GuestRpc:



Proceedings of AMTA 2018, vol. 2: MT Users' Track

Boston, March 17 - 21, 2018 | Page 104



Case Studies



Case Study 1: Internal Dept, MTPE



MemoQ as CAT tool $(\checkmark$ (\checkmark)

(<)

Numerous MT connectors Currently on MS Hub SMT EN<>FR, IT, DE, ES, PTBR

One domain, life sciences Any SMT or NMT solution must be customizable

OpenNMT adaptation shows markedly improved scores



ITEM	соѕт	SAVINGS
Connector	0	
MT Usage	0	
Engine Cost (\$1000 per locale pair per year)	\$8000	
Vendor discounts (100K new words per year* 8 locale pairs* .01 per word)		\$8000

Case Study 1 ROI **Calculations**

By how much does NMT need to win in order to move now? (⁄)

ί.	1
C	′ /

How can we put a price on this?

How much volume? What languages?

(<) NOTE: How likely is additional .01 per word for each locale pair? What additional discount does it represent? welocalize doing things differently For rate of .15, that's an additional 7%.



Case Study 2, Tech Support, Raw MT

 (\checkmark)

 (\checkmark)



All possible language combinations, i.e. over 50 languages UGC – prone to slang, typos, incorrect formatting MT embedded into chat application How important is lexical coverage? How many MT connectors does the chat application support? If several, can you mix and match? If you deploy several, what's the administrative overhead of licensing and retraining from several different MT providers? Is normalization taking place?

What is the minimum allowable level of quality for the lowest cost?



Case Study 3, Enterprise, MTPE



Enterprise level TMS
Currently on MS Hub
Each MT connector costs money and has to be vetted by TMS provider
Many (but not all) languages do better in NMT

- What business problem are we solving TAT, quality, cost of delivery? How will the move to NMT be a game changer?
- Split the languages amongst the connectors or only move when you can do all of them?
 As in case study 1, what's the cost of each connector relative to the expected volume, increased quality and expected discount by moving to neural?





What Else Can We Do with Neural Technology?





What Else Can We Do?

NLG (Natural Language Generation) with (\checkmark) subsequent NMT



Sentiment analysis



 \checkmark

Predictive analytics for localization program management and linguist selection



Predictive input



Machine learning for LQA and evaluation of source

Document summarization \checkmark



Thank you

