Booking.com NMT a OpenNMT use case

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Presentation Outline

- MT use cases at Booking.com
- Pipeline and Standard Architecture
- Evaluation pipeline
- Domain Adaptation for User Generated Content (UGC)
- Translation challenges
- Production pipeline
- Recommendations & feature requests
- References

Use cases at Booking.com

2/3 of daily bookings on Booking.com is made in a language other than English

… thus it is important to have **locally relevant content at scale**

How Locally Relevant?

Allow partners and guests to **consume and produce content in their own language**

- Hotel Descriptions
- Customer Reviews
- Customer Service Support

Why At Scale?

- **One Million+ properties** and growing very fast
- **Frequent change requests** to update the content
- **43 languages** and more
- New user-generated **customer reviews / tickets** every second

Main use cases at Booking.com

- Hotel & Room Descriptions
  - 50% human translation coverage
  - 90% demand coverage
  - Average of 10M parallel sentences for high demand languages

- User Reviews
  - No Translation coverage
  - No In-Domain data

Pipeline and Standard Architecture

Preprocessing	Training	Translation	Post Processing
- Data Cleaning - Handling numbers and Named Entities* - OpenNMT preprocessing + extra domain related features**	-Seq to seq arch, described in the following slide -Domain Fine-Tuning*	- Determining best combination to translate - OpenNMT Translate	- OpenNMT post processing - Numbers and Named Entities post processing* - Predicting errors in MT text

Evaluation
- Automatic Evaluation - Human Evaluation

* For some use cases
** Depending on language / use case

Pipeline and Standard Architecture

NMT

Data Preprocessing	
Input text unit	Lowercased BPE
Tokenization	Aggressive, with case features
Max. sent length	50 units
Vocab Size	30,000-50,000 * * Joint or Separate

Architecture ** Variant of (Bahdanau et al)	
Input dim	1000
RNN dim	1000
# of hidden layers	Encoder: 4 Decoder: 4
Attention mechanism	Global
RNN Type	LSTM ** Bidirectional encoder
Residual connections	Yes

Optimization ** Standard pipeline	
Optimizer	SGD
Learning rate decay	0.7
Decay strategy	Validation perplexity increase or Epoch > 20
Stopping Criteria	Based on validation perplexity
Dropout rate	0.3
Max Batch size	120

Others	
Inference Beam size	5
GPU	Nvidia P100

Evaluation Pipeline

- BLUE score Evaluations for model development

- Human Evaluation:
  - Adequacy and Fluency checks before model deployment
  - Periodic checks or random samples
  - Biased sample evaluation:
    - Score recent production translations using our in-house error detection model
    - Send lowest scored sentences for human evaluation

Domain Adaptation for UGC (Data)

- Little to no in-domain data.

- In addition to our hotel descriptions data, available external open data is used including data from:
  - Movie subtitles
  - Wikipedia
  - TED talks
  - New commentary
  - EuroParl

Domain Adaptation for UGC (Data)

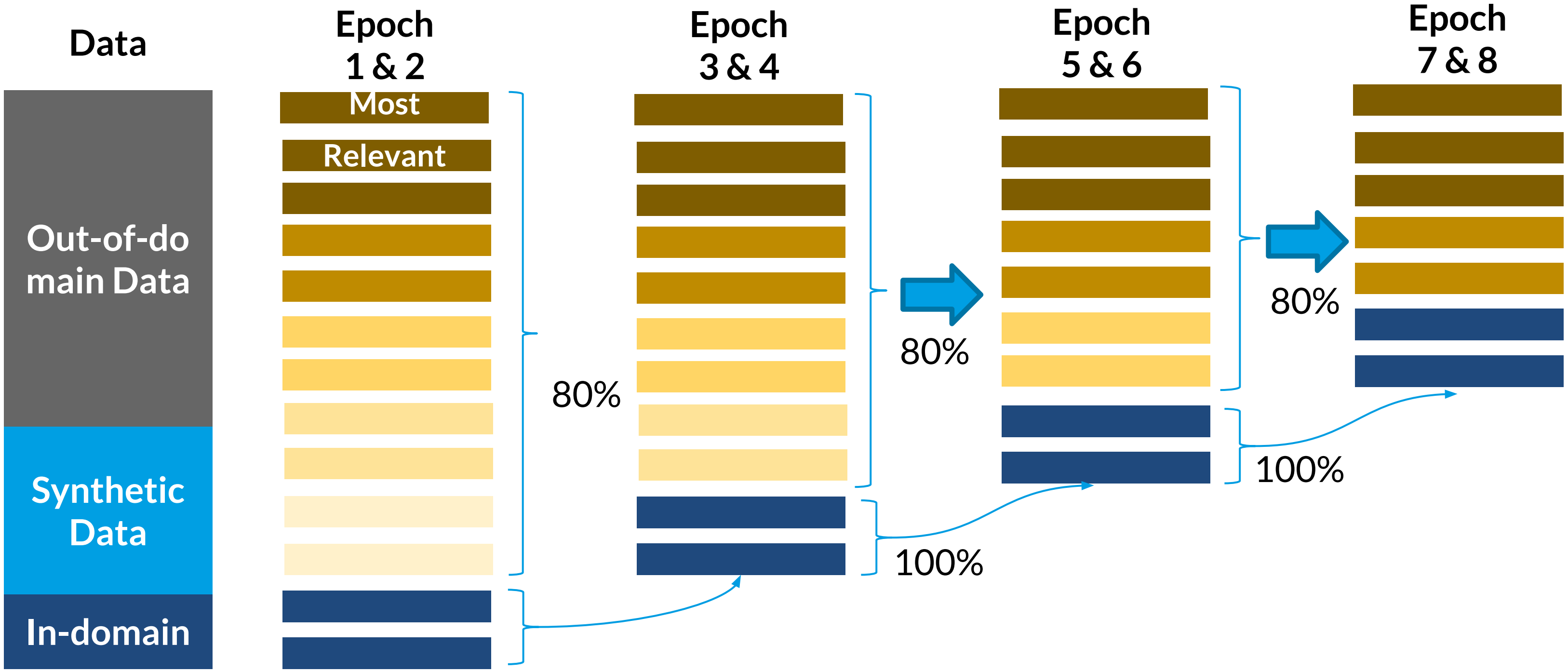
- Synthetic Data

- We then use either Gradual Downsampling (Wees et al.) or Fine Tuning for domain adaptation

Gradual Downsampling approach

Data	Idea	Methodology
Out-of-Domain Data	Use in-domain and general data language models to select most relevant sentences from general data	Bilingual Cross Entropy Difference (Axelrod et al) - To select sentences that are most similar to in-domain but different to out-of-domain.
Synthetic Data	Use large amount of mono-lingual in-domain data to create some synthetic in-domain data	Back translate target language in-domain data into source by reversing our MT model (Sennrich et al.). (Ranked Randomly)
In-domain Data	Create a small amount of in-domain corpus as well, to test for additional impact	Human Translation

Gradual Downsampling approach



Fine-Tuning Approach

- Train with Open data + in house out of domain data.
- Wait until the model converges
- Fine tune with few in-domain data samples (reviews)

Domain Adaptation for UGC

Gradual Downsampling	Fine-Tuning
Faster iterations	Takes time to get the General Model trained
Trained for specific use case from the beginning	Can be adapted to multiple use cases
Applicable without In-domain parallel data	Needs In-domain parallel data
Less accurate	More Accurate

- General purpose model or Gradual downsampling model? (without in-domain data)
  - Not Answered yet!

Translation Challenges

- Numbers Translations
  - Solution: Placeholders for distances, time, currency, date, etc,.
- Named Entities (NE) Translations
  - Solution: NE placeholders and NE tagging models (still tricky)
- Rare words Translations
  - On average our system is better than a general purpose
  - Not always the case when it comes to rare words, even if you have millions of in-domain data
  - Training with general purpose data and fine tuning with domain data helps

Translation Challenges

- Repetitions and Omissions:
  - Incorporation of more general language models for encoder/decoder initialization and training (Ramachandran et al.)
  - OpenNMT support is needed!

- Inaccurate source language (grammar and punctuation)

Translation Challenges

- Context handling
  - Mainly gender issues:
    - Property type co-reference can be male/female in some languages. This depends mainly on the property type gender in the previous sentence
    - We use property type features for some languages
  - Exploiting context from previous/next sentences (Bawden et al.)
  - OpenNMT Support is needed!

Production Pipeline

- ZeroMQ server provides more flexibility however it's not compatible with our HTTP based infrastructure.

- We use our batched version of the REST server:
  - We have our own production preprocessing functionalities.
  - The OpenNMT REST server is used then for the translation.
  - It was necessary to have this separation to be able to add our crafted features during preprocessing and use the server only for translation.

Recommendations & Feature requests

- Instance weighting
  - Explicit Instance weighting that is incorporated in the loss function with the possibility of having negative weights (wrong translations)
  - Resample data between epochs/batches and adapt instance weights based on validation performance
  - Wang et al, showed some instance weighting and adaptive weighting approaches that could be of inspiration

Recommendations & Feature requests

- Always start with models trained on all the available data

- Our recent experiments shows significantly better results when we used the “Big Transformer” architecture as described by Vaswani et al. (lua version support?)

Recommendations & Feature requests

- Multi-encoder support
  - Make use of our available features for sequence to sequence problems (context, images, etc,.)

- More support for Tensorflow version is more crucial for production systems
  - Tensorflow has more proper versioning unlike torch
  - Installation is more easier for production (lua torch is more optimized for research and easier to install for user level)
  - Tensorflow is more supported in more production environments

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Thank you!

Any Questions?

Our MT team is hiring a new NLP Data Scientist!

Contact me if you are interested

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