

Baseline

A Library for Rapid Modeling,
Experimentation and Development of Deep
Learning Algorithms targeting NLP

Daniel Pressel, Sagnik Ray Choudhury, Brian Lester, Yanjie Zhao, Matt
Barta



A U S T R A L I A
NLP OSS Workshop @ ACL 2018

Baseline: A Deep NLP library built on these principles

- simplicity is best
 - Minimal dependencies, effective design patterns
 - Add value but never detract from a DL framework
 - A la carte design: take only what you need
- baselines should be strong, reflect NLP zeitgeist
- boilerplate code for training deep NLP models should be baked in
 - Flexible builtin loaders, datasets, embeddings, trainers, evaluation, baselines
 - 80% use-case should be trivial, the rest should be as simple as possible



Baseline: A Deep NLP library built on these principles

- experiments should be automatically reproducible and tracked
 - Models, hyper-parameters
 - Standard metrics and datasets facilitate better model comparisons
- research benefits from rapid development, automatic deployment
 - Training should be efficient, work on multiple GPUs where possible
 - Library should provide reusable components to accelerate development
- go where the user is: do not make them come to you!



Use Baseline code base if you want...



- A reusable harness to train models and track experiments
 - Focus on the models instead of the boilerplate
 - Define your configuration with a model and a configuration file
- Strong, well-tested deep baselines for common NLP tasks
 - Classification
 - Tagging
 - Seq2seq
 - Language Modeling
- Support for your favorite DL framework
 - TensorFlow, PyTorch and DyNet all supported
- Reusable components to build your own SoTA models

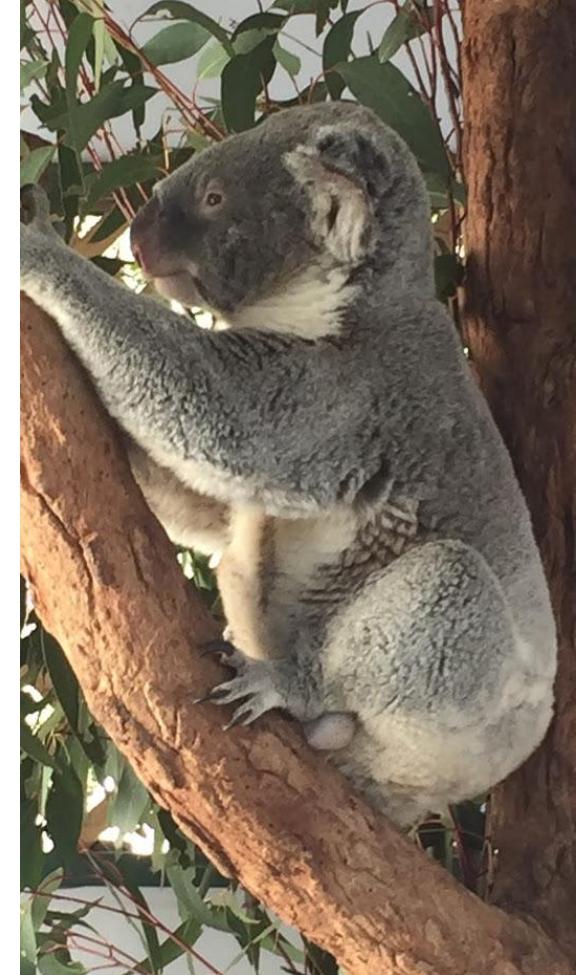
Use Baseline code base if you want...

- A Leaderboard to track progress of your models and HP configurations
- Support for auto-deployment into production (caveat: TF only)
- Built-in dataset and embedding downloads
- Strong models, with addon support for...
 - Transformer
 - ELMo
 - Gazetteers



Future

- More tasks!
- Even stronger baselines!
- Faster training!
- Recipes with pre-training using LMs
- local experiment repo, streaming support
 - For live monitoring and control from a frontend
- native framework optimized readers
- Better integration with other OSS projects
- HPO utilities
- Open experiment server
- Web interface for launching/management



Want to help build?

- PRs welcome!
- Codebase:
 - <https://github.com/dpressel/baseline>
- Public addons:
 - <https://github.com/dpressel/baseline/tree/master/python/addons>
- Contact Info
 - dpressel@gmail.com, @DanielPressel



Refs: Representations, Cross-Task

- *Distributed Representations of Words and Phrases and their Compositionality* (Mikolov, Sutskever, Chen, Corrado, Dean)
 - <https://arxiv.org/abs/1310.4546>
- *Exploiting Similarities among Languages for Machine Translation* (Mikolov, Le, Sutskever)
 - <https://arxiv.org/abs/1309.4168>
- *Efficient Estimation of Word Representations in Vector Space* (Mikolov, Chen, Corrado, Dean)
 - <https://arxiv.org/abs/1301.3781>
- *Deep contextualized word representations* (Peters et al)
 - <https://export.arxiv.org/pdf/1802.05365>
- *Finding Function in Form: Compositional Character Models for Open Vocabulary Word Representation* (Ling et al)
 - <https://arxiv.org/pdf/1508.02096.pdf>
- *Natural Language Processing (Almost) from Scratch* (Collobert et al)
 - <http://jmlr.org/papers/volume12/collobert11a/collobert11a.pdf>
- *Enriching Word Vectors with Subword Information* (Bojanowski, Grave, Joulin, Mikolov)
 - <https://arxiv.org/abs/1607.04606>

Refs: Classification and Neural Architecture

- *Convolutional Neural Networks for Sentence Classification (Kim)*
 - <https://arxiv.org/abs/1408.5882>
- *Rethinking the Inception Architecture for Computer Vision (Szegedy)*
 - <https://arxiv.org/abs/1512.00567>
- *Going Deeper with Convolutions (Szegedy et al)*
 - <https://arxiv.org/abs/1409.4842>
- *Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift (Ioffe/Szegedy)*
 - <https://arxiv.org/abs/1502.03167>
- *Hierarchical Attention Networks for Document Classification (Yanh et al)*
 - <https://www.microsoft.com/en-us/research/publication/hierarchical-attention-networks-document-classification/>
- *Deep Residual Learning for Image Recognition (He, Zhang, Ren, Sun)*
 - <https://arxiv.org/pdf/1512.03385v1.pdf>

Refs: Tagging

- *Learning Character-level Representations for Part-of-Speech Tagging (dos Santos, Zadrozny)*
 - <http://proceedings.mlr.press/v32/santos14.pdf>
 - <https://rawgit.com/dpressel/Meetups/master/nlp-reading-group-2016-03-14/presentation.html#1>
- *Boosting Named Entity Recognition with Neural Character Embeddings (dos Santos, Cicero and Victor Guimaraes)*
 - <http://www.aclweb.org/anthology/W15-3904>
 - <https://rawgit.com/dpressel/Meetups/master/nlp-reading-group-2016-03-14/presentation.html#1>
- *Neural Architectures for Named Entity Recognition (Lample et al)*
 - <https://arxiv.org/abs/1603.01360>
- *End-to-end Sequence Labeling via Bi-directional LSTM-CNNs-CRF (Ma, Hovy)*
 - <https://arxiv.org/abs/1603.01354>
- *Reporting Score Distributions Makes a Difference: Performance Study of LSTM-networks for Sequence Tagging (Reimers, Gurevych)*
 - <http://aclweb.org/anthology/D17-1035>
- *Design Challenges and Misconceptions in Neural Sequence Labeling (Yang, Liang, Zhang)*
 - <https://arxiv.org/pdf/1806.04470.pdf>

Refs: Encoder Decoders

- *Sequence to Sequence Learning with Neural Networks* (Sutskever, Vinyals, Le)
 - <https://arxiv.org/abs/1409.3215>
- *Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation* (Cho et al)
 - <https://arxiv.org/abs/1406.1078>
- *Neural Machine Translation by Jointly Learning to Align and Translate* (Bahdanau, Cho, Bengio)
 - <https://arxiv.org/abs/1409.0473>
- *Attention Is All You Need* (Vaswani et al)
 - <https://arxiv.org/pdf/1706.03762.pdf>
- *Show and Tell: A Neural Image Caption Generator* (Vinyals, Toshev, Bengio, Erhan)
 - <https://arxiv.org/pdf/1411.4555v2.pdf>
- *Effective Approaches to Attention-based Neural Machine Translation* (Luong, Pham, Manning)
 - https://nlp.stanford.edu/pubs/emnlp15_attn.pdf

Refs: Language Modeling

- *Recurrent Neural Network Regularization (Zaremba, Sutskever, Vinyals)*
 - <https://arxiv.org/abs/1409.2329>
- *Character-Aware Neural Language Models (Kim, Jernite, Sontag, Rush)*
 - <https://arxiv.org/abs/1508.06615>
- *Exploring the Limits of Language Modeling (Jozefowicz, Vinyals, Schuster, Shazeer, Wu)*
 - <https://arxiv.org/pdf/1602.02410v2.pdf>

OPENSEQ2SEQ

Oleksii Kuchaiev, Boris Ginsburg, Igor Gitman, Vitaly Lavrukhin, Carl Case,
Paulius Micikevicius, Jason Li, Vahid Noroozi, Ravi Teja Gadde



Overview

1. Toolkit for building sequence to sequence models

- ✓ Neural Machine Translation
- ✓ Automated Speech Recognition
- ✓ Speech Synthesis

2. Mixed Precision training*



3. Distributed training: multi-GPU and multi-node

4. Extendable

5. Open-source: <https://github.com/NVIDIA/OpenSeq2Seq>

* Micikevicius et al. “Mixed Precision Training” *ICLR 2018*

Usage & Core Concepts

Core concepts:

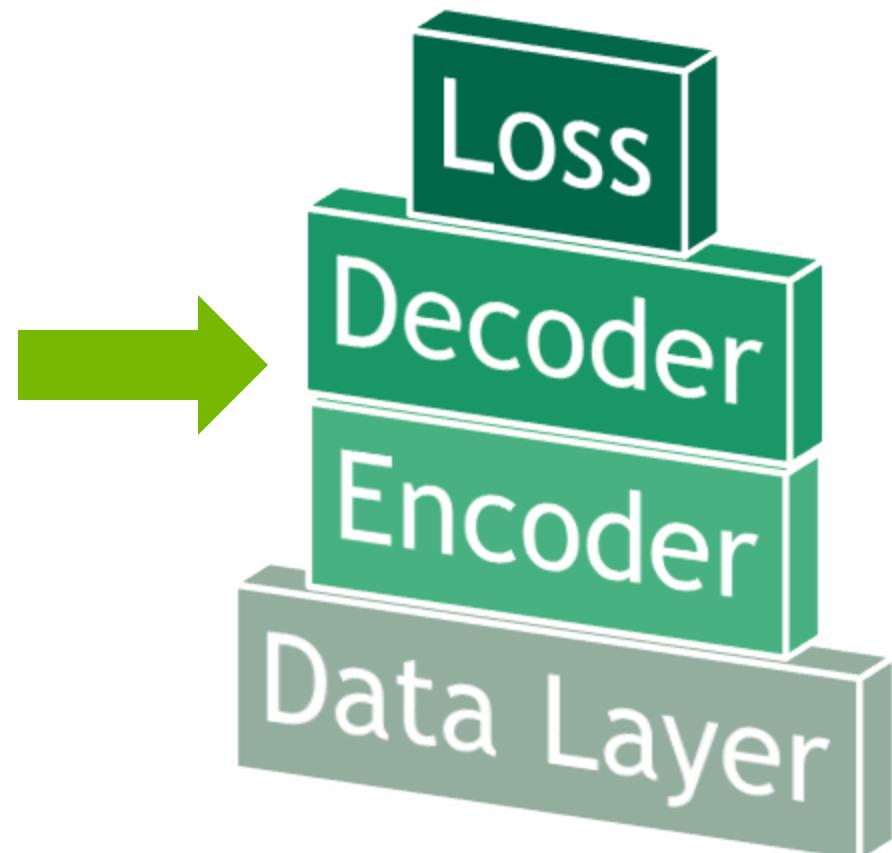
- Data Layer
- Encoder
- Decoder
- Loss

User can mix different encoders and decoders

Flexible Python-based config file

```
42     "encoder": BidirectionalRNNEncoderWithEmbedding,  
43     "encoder_params": {  
44         "initializer": tf.glorot_uniform_initializer,  
45         "core_cell": tf.nn.rnn_cell.LSTMCell,  
46         "core_cell_params": {  
47             "num_units": 512,  
48             "forget_bias": 1.0,  
49         },  
50         "encoder_layers": 2,  
51         "encoder_dp_input_keep_prob": 0.8,  
52         "encoder_dp_output_keep_prob": 1.0,  
53         "encoder_use_skip_connections": False,  
54         "src_emb_size": 512,  
55         "use_swap_memory": True,  
56     },  
57  
58     "decoder": RNNDecoderWithAttention,  
59     "decoder_params": {  
60         "initializer": tf.glorot_uniform_initializer,  
61         "core_cell": tf.nn.rnn_cell.LSTMCell,  
62         "core_cell_params": {  
63             "num_units": 512,  
64             "forget_bias": 1.0,  
65         },  
66         "decoder_layers": 2,
```

Seq2Seq model



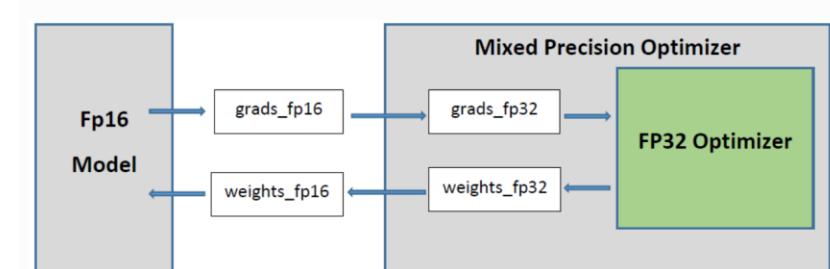
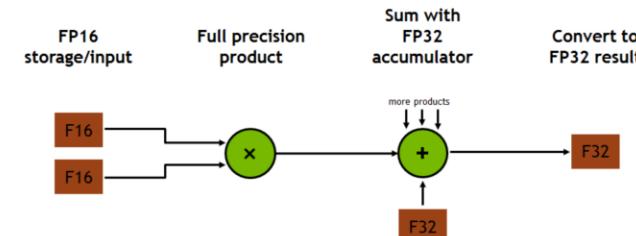
Mixed Precision Training - *float16*

- ✓ Train SOTA models faster and using less memory
- ✓ Keep hyperparameters and network unchanged

Mixed Precision training*:

1. Use NVIDIA's Volta GPU (for *Tensor Core math*)
2. Maintain *float32* master copy of weights for weights update.
3. Use the *float16* weights for forward and back propagation
4. Apply loss scaling while computing gradients to prevent underflow during backpropagation

Tensor Core math

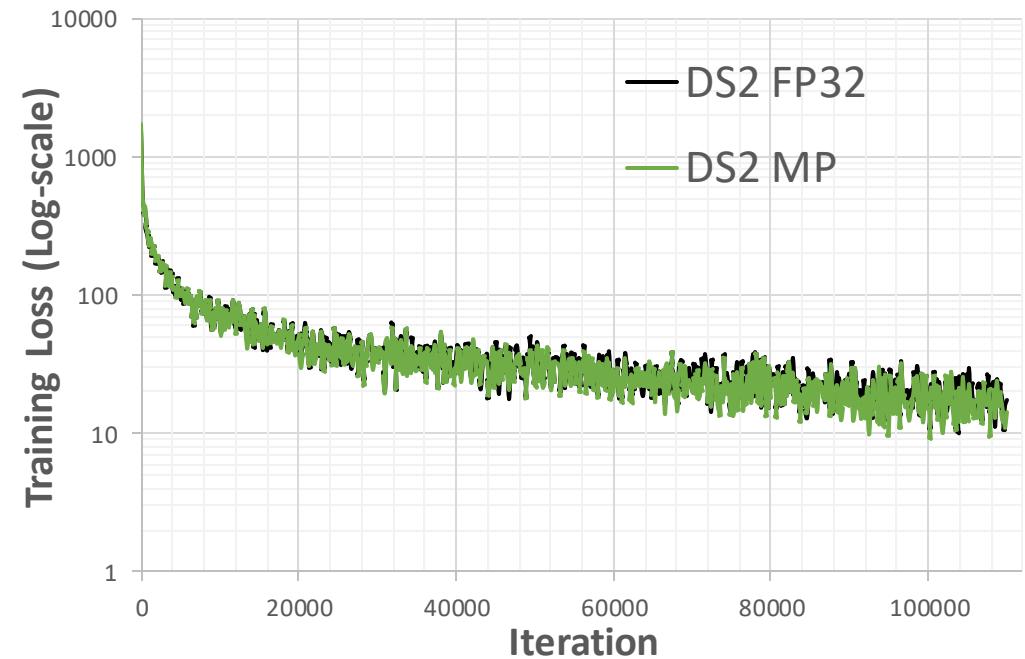
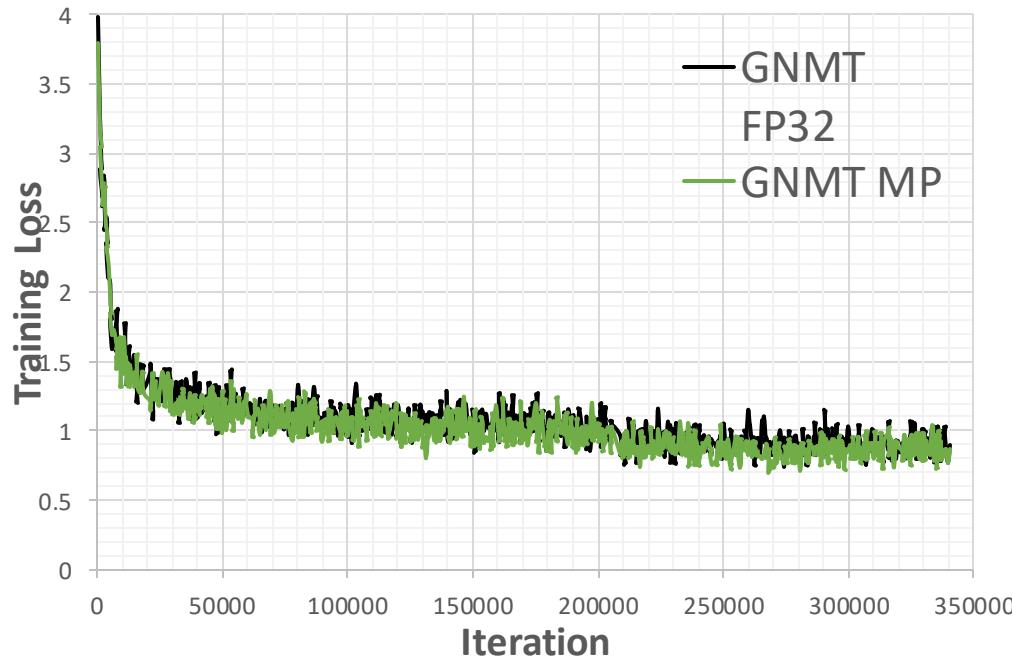


"Mixed precision" optimizer wrapper around any TensorFlow optimizer.

OpenSeq2Seq implements all of this on a base class level

* Micikevicius et al. "Mixed Precision Training" ICLR 2018

Mixed Precision Training



Convergence is the same for *float32* and *mixed precision* training. But it is faster and uses about 45% less memory

Summary

... ⇌ ...

OpenSeq2Seq currently implements:

NMT: GNMT, Transformer, ConvSeq2Seq

ASR: DeepSpeech2, Wav2Letter

Speech Synthesis: Tachotron

Makes mixed precision and distributed training easy!

Code, Docs and pre-trained models:

<https://github.com/NVIDIA/OpenSeq2Seq>

Contributions are welcome!





Scalable Understanding of Multilingual Media

Open-source Software for Multilingual Media-Monitoring

Ulrich Germann¹, Renārs Liepiņš², Didzis Gosko², Guntis Barzdins^{2,3}

¹ University of Edinburgh; ² Latvian News Agency; ³ University of Latvia



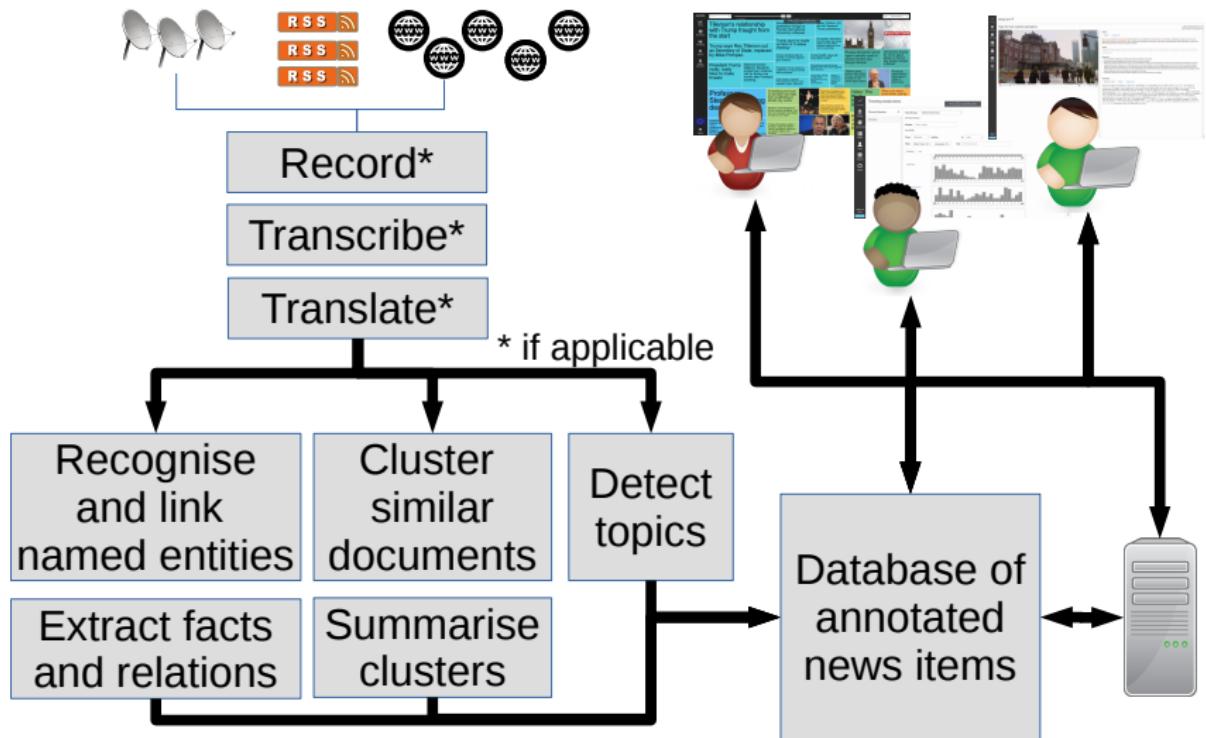
This work was conducted within the scope of the Research and Innovation Action SUMMA, which has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 688139.

Use Case 1: BBC Monitoring



<https://www.facebook.com/BBCMonitoring/photos>

Workflow



NLP Technologies in SUMMA

ASR	Training: Kaldi [1]; transcription: CloudASR [2]
MT	Marian [3]
NE Recognition	Improved TurboEntityRecognizer [4]
NE Linking	Improved TurboParser [4]
Topic Detection	Hierarchical attention model [5]
Doc. Clustering	Online algorithm by Aggarwal & Yu [6]
Summarization	Extractive algorithm by Almeida et al. [7]
Semantic Parsing	AMR parser by Damonte et al. [8]
Timeline Creation	Cornegruta & Vlachos [9]
KB Population	Paikens et al. [10]

Could You Implement Your Technology in X?

Could You Implement Your Technology in X?



imgflip.com

So how did we do it?

... come see the poster!

References

- [1] D. Povey et al., 2011. "The Kaldi Speech Recognition Toolkit". In: *Proc. ASRU*.
- [2] O. Klejch et al., 2015. "CloudASR: Platform and Service". In: *Proc. Int'l. Conf. on Text, Speech, and Dialogue*.
- [3] M. Junczys-Dowmunt et al., 2018. "Marian: Fast Neural Machine Translation in C++". In: *ACL Demonstration Session*.
- [4] A. F. Martins et al., 2009. "Concise Integer Linear Programming Formulations for Dependency Parsing". In: *Proc. ACL-IJCNLP*.
- [5] Z. Yang et al., 2016. "Hierarchical Attention Networks for Document Classification". In: *Proc. NAACL*.
- [6] C. C. Aggarwal & P. S. Yu, 2006. "A Framework for Clustering Massive Text and Categorical Data Streams". In: *Proc. SIAM Int'l. Conf. on Data Mining*. SIAM.
- [7] M. B. Almeida & A. F. Martins, 2013. "Fast and Robust Compressive Summarization with Dual Decomposition and Multi-Task Learning." In: *ACL*.
- [8] M. Damonte et al., 2017. "An Incremental Parser for Abstract Meaning Representation". In: *Proc. EACL*.
- [9] S. Cornegruta & A. Vlachos, 2016. "Timeline Extraction Using Distant Supervision and Joint Inference". In: *Proc. EMNLP*.
- [10] P. Paikens et al., 2016. "SUMMA at TAC Knowledge Base Population Task 2016". In: *Proc. TAC*.

OpenNMT

Open Source solution for Research ... and Industry

Sasha Rush, Harvard NLP, **Jean Senellart** and Guillaume Klein, SYSTRAN

Vincent Nguyen, UBIQUUS

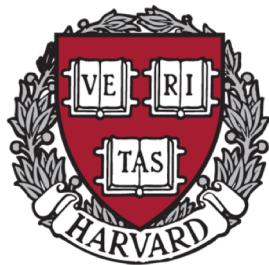


What is OpenNMT?

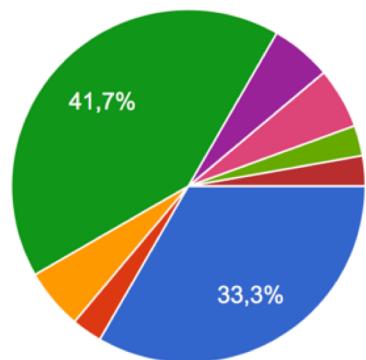


- Generic framework for seq2seq Neural Machine Translation
- ... extending to many other applications
 - End-to-end Speech recognition
 - Img2Text
 - Dialog systems
 - Grammar checking

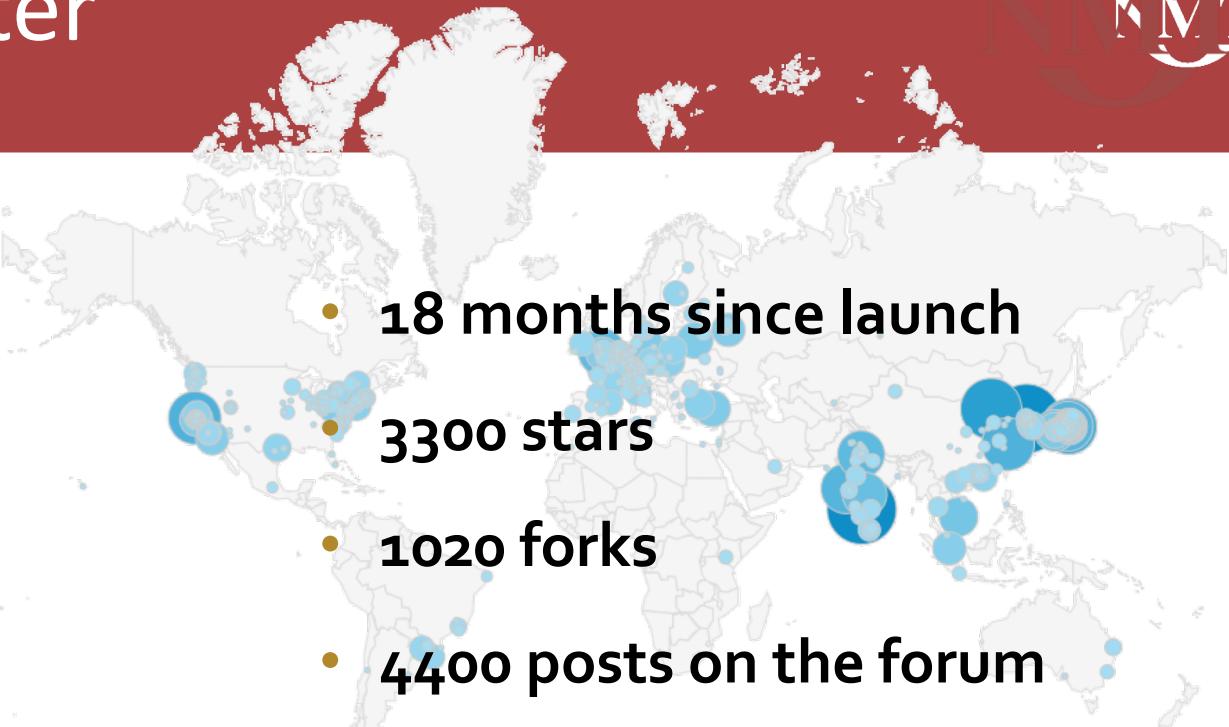
OpenNMT - 18 months after



[ubiqus]



- Developer
- Linguist, Language specialist
- Translator, or Translation Project Manager
- Researcher / Academics
- Independent Expert
- Executive
- Hobbyist
- First two and last
- Software architect (researcher + de...)

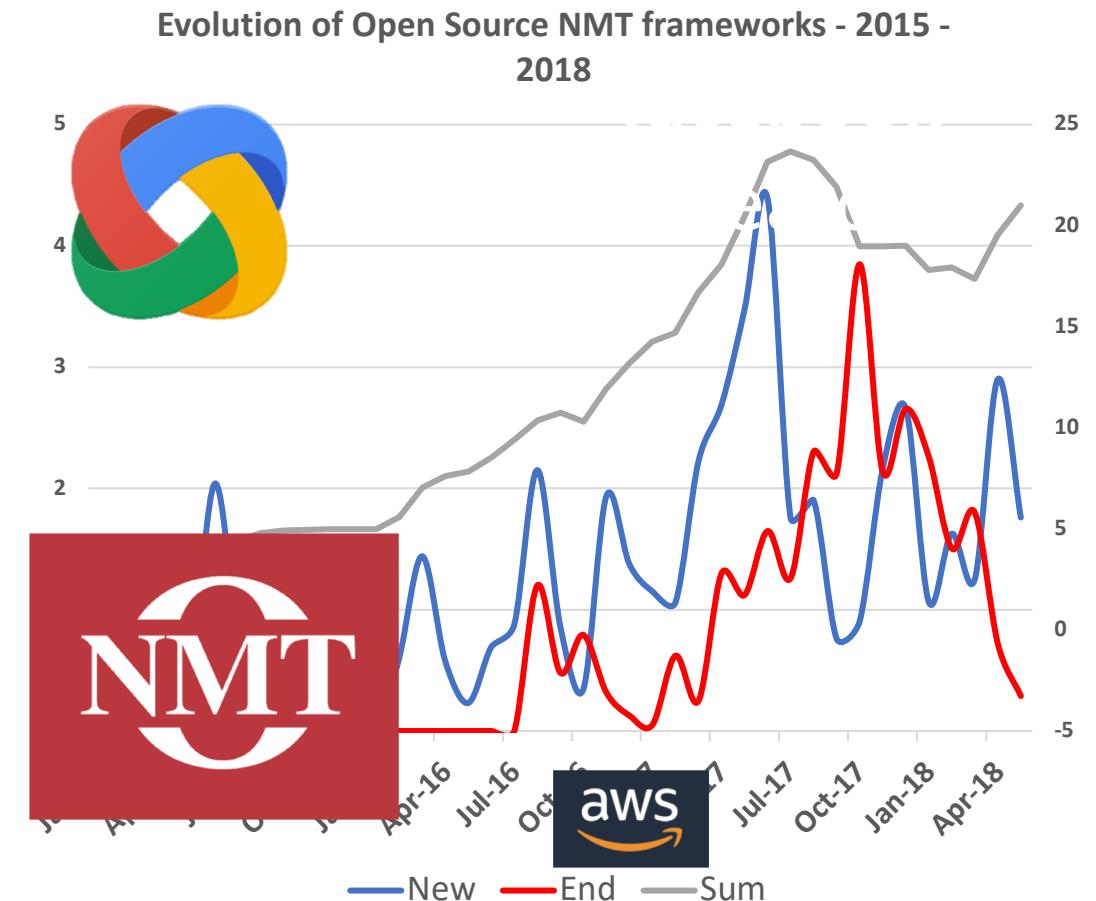


- 18 months since launch
 - 3300 stars
 - 1020 forks
 - 4400 posts on the forum
 - 100+ contributors (15 active)
 - 18 major releases
 - 6 complete code refactoring
 - 600 unit tests
- Only ... 5000 lines of code

NMT Openness



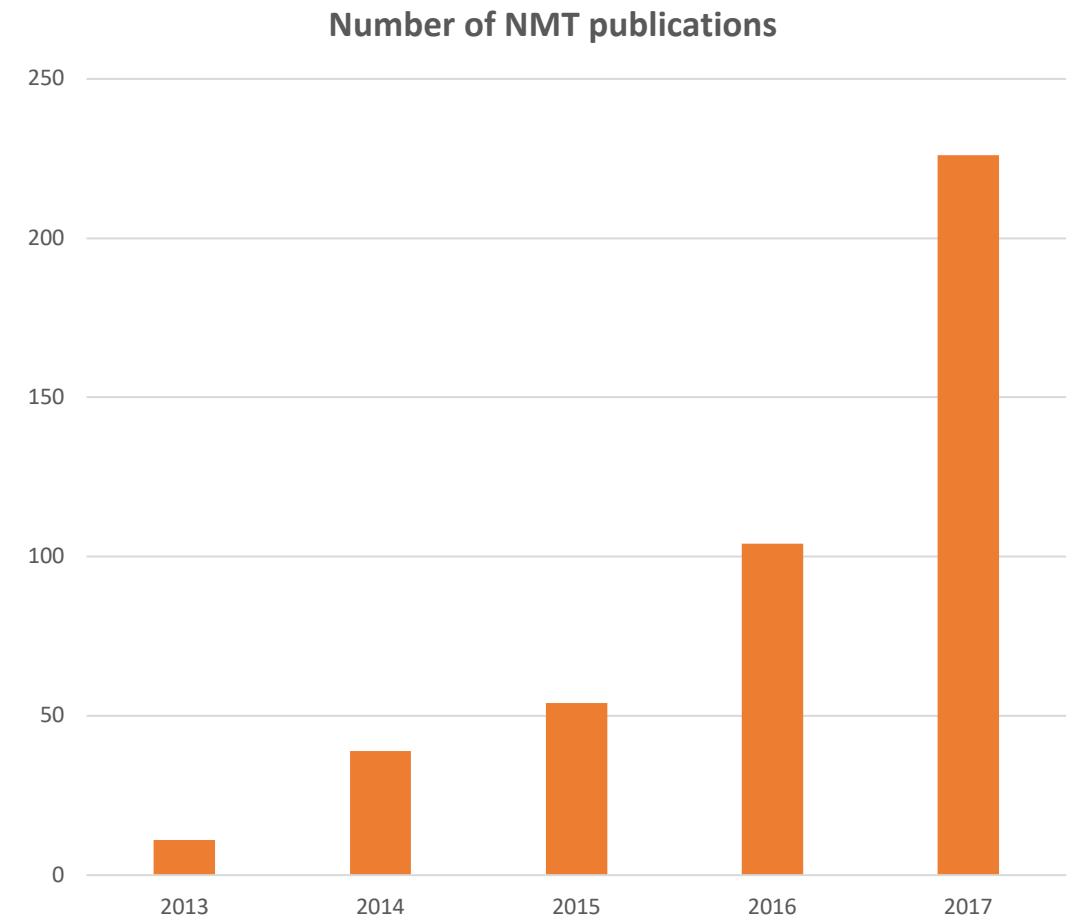
- About 2 new Open Source projects per month
 - Dominated by industry
- Systematic Publications for industrial deployments
 - GNMT, PNMT, Wipro, ...
 - Microsoft
- Proof by number
 - DeepL, Omniscient



Very fast changing technology

- Huge number of publications

- Major paradigm change
 - RNN
 - CNN
 - Attention-Based
 - ...

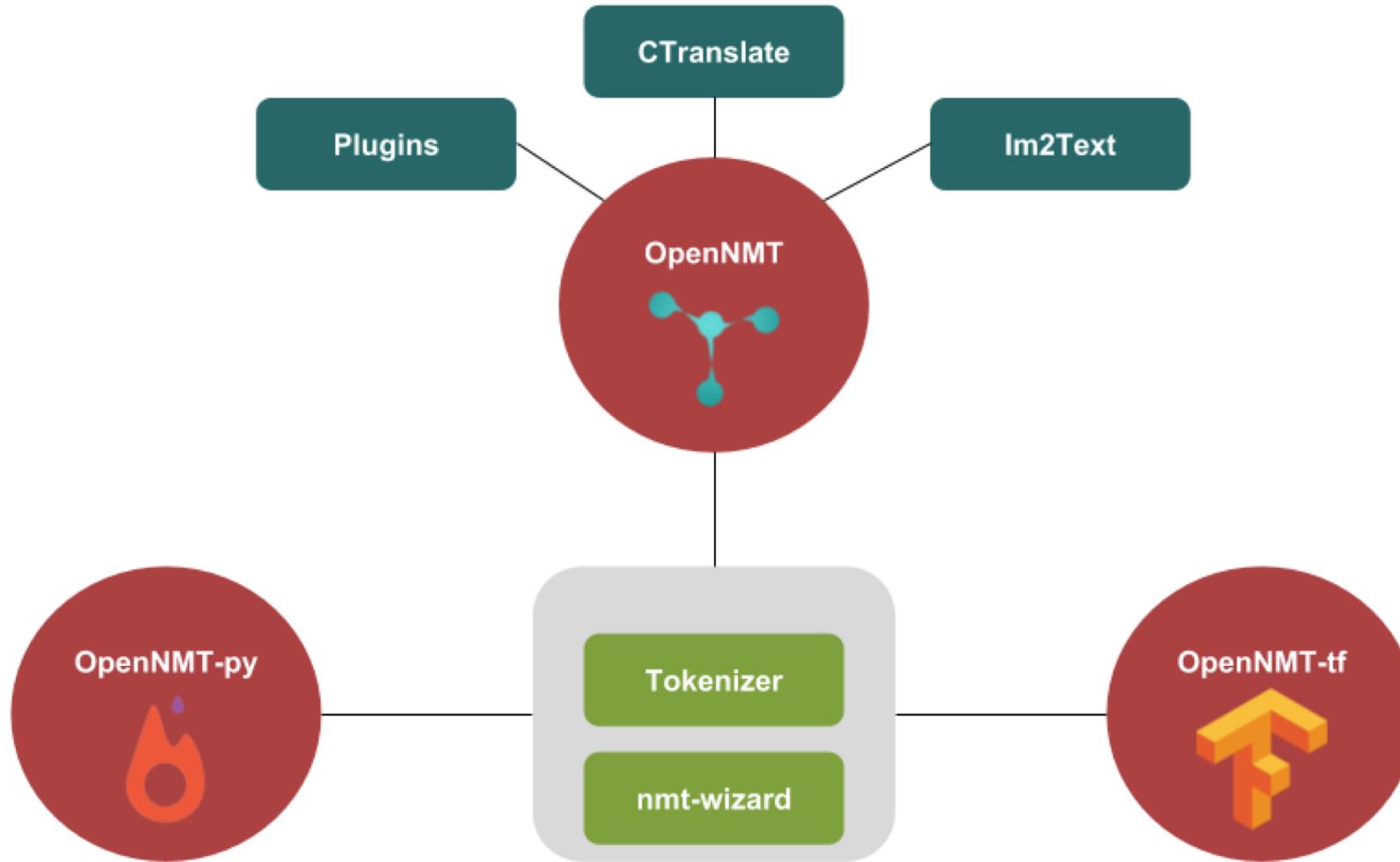


Open Source survival rules

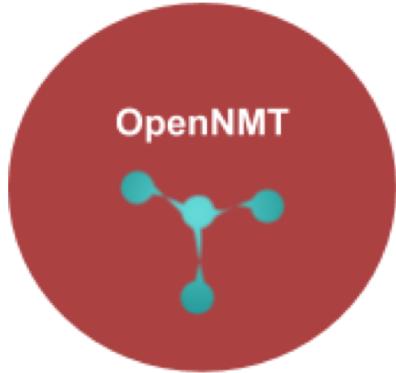


- Open Source is not enough, the community expects:
 - Keep-up with new frameworks
 - Daily support
 - Sharing of data, recipes and good practices
 - Sharing of negative findings
 - Integration of the latest, brightest publications
 - Modularity
 - ... Stability
- A lot of work – why are we fighting for this?

Current OpenNMT landscape

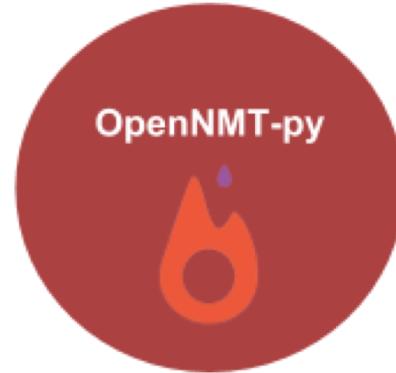


An evolving roadmap



maintenance mode:

same level of support
but no major changes to
be expected



research-oriented:

flexible
hackable



production-oriented:

super-fast
robust
clean APIs

From Research – to ... reproduction – to ... production



■ Come and see our poster!

NMT

The Annotated Transformer

Alexander M. Rush
Harvard University
<https://github.com/harvardnlp/annotated-transformer>

Context

A major goal of open-source NLP is to quickly and accurately reproduce the state-of-the-art new work. We believe that the community can easily use and modify. While most papers publish enough details for replication, it still may be difficult to achieve good results in practice. This paper presents a worked exercise of paper reproduction with the goal of implementing the recent Transformer model. The replication exercise aims at simple code structure that follows closely with the original work, while achieving an efficient usable system.

Goal

Figure: Visualization of one-layer of multi-headed attention constructed in the tutorial.

Example: Optimizer

We used the Adam optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.98$ and $\epsilon = 10^{-9}$. We varied the learning rate over the course of training, according to the formula:

$$\text{lr} = d_{\text{model}}^{-0.5} \cdot \min(\text{step_num}^{-0.5}, \text{step_num} \cdot \text{warmup_steps}^{-1})^{\frac{1}{2}}$$

This corresponds to increasing the learning rate linearly for the first warmup_steps training steps, and decreasing it thereafter proportionally to the inverse square root of the step number. We used $\text{warmup_steps} = 4000$.

Example: Embeddings

In this work, we use sine and cosine functions of different frequencies:

$$PE_{pos,i} = \sin(pos/10000^{0.025*i}) \cdot P_{pos,i}^{(2d)} + \cos(pos/10000^{0.025*i}) \cdot P_{pos,i}^{(2d+1)}$$

where pos is the position and i is the dimension. That is, each dimension of the positional encoding corresponds to a sinusoid. The wavelengths form a geometric progression from $10000^{0.025} \approx 48.9$ to $10000^{0.025 * (d-1)} \approx 0.03$. We chose this scheme because it allows the model to easily learn to attend by relative positions, since for any fixed offset k , $PE_{pos+k,i}$ can be represented as a linear function of $PE_{pos,i}$.

Example: Masking

We also modify the self-attention sub-layer in the decoder stack to prevent positions from attending to subsequent positions. This masking, combined with fact that the output embeddings are offset by one position, ensures that the predictions for position i can depend only on the known outputs at positions less than i .

Style

The Annotated Transformer alternates the verbatim text of the paper with code and graphics. The aim is to allow the text to give the narrative, but to show how every statement transfers to code. Each code snippet also includes a toy visualization demonstrating its use. Here we show three examples from the blog post.

Release

harvardnlp
SYSTRA beyond language

Code

```
class NoOpt:
    ...
    def rate(self, step=None):
        """Compute the lr for 'step' above"""
        if step is None:
            step = self.step
        return self.factor * (
            self.model_size ** (-0.5))
        * min(step ** -0.5, step * self.varamp ** (-1.5))

    @property
    def lr(self):
        return self.rate()

    @lr.setter
    def lr(self, value):
        self.step = value

    def step(self):
        self.step += 1
        self.varamp *= self.varamp_rate
        self.factor *= self.factor_rate
```

Acknowledgments

Thanks to Guillaume Klein and Jean Senellart from Systran and Vincent Nguyen from Ubiquis for testing and work on OpenNMT, and to Jakob Uszkoreit and the other authors of this paper for letting me experiment with their words.