Exploring the Limits of Transfer Learning with a unified Text-to-Text Transformer

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Elements and images borrowed from Raffel et al., 2019

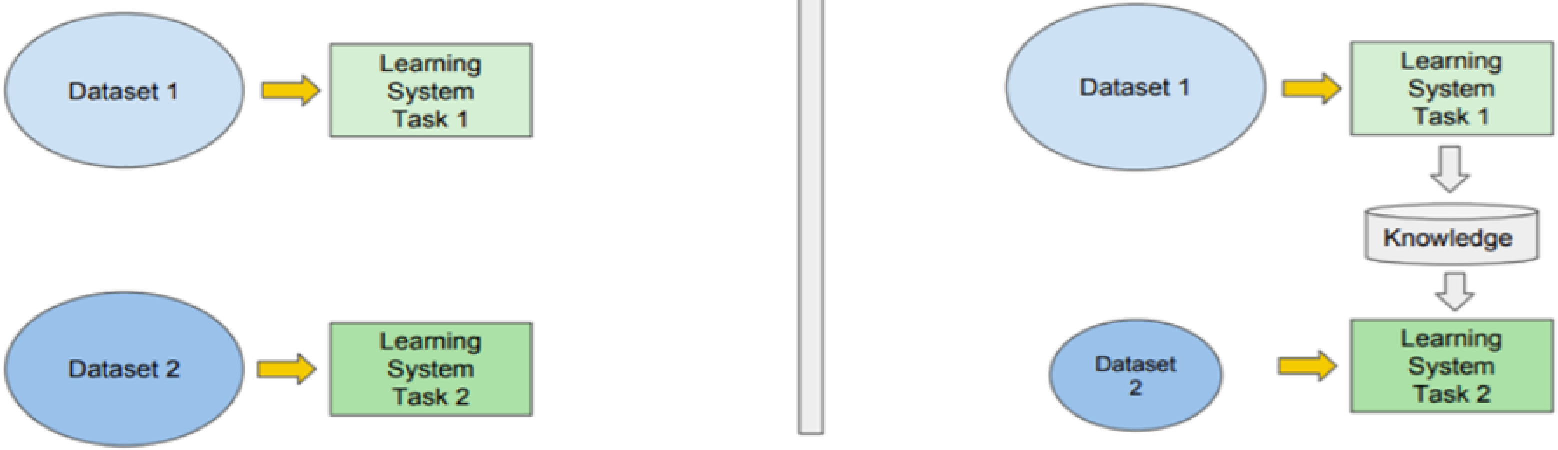
Transfer Learning: Background

- Pre-train a model on a data-rich task (Unsupervised)
  e.g. Word2vec, Glove (Mikolov et al., 2013a,b)
- Fine tune on a downstream task (Supervised)
- Pre-training gives a model “general-purpose abilities” that can be “transferred” to downstream tasks

Traditional ML vs Transfer Learning

- Isolated, single task learning:
  - Knowledge is not retained or accumulated. Learning is performed w.o. considering past learned knowledge in other tasks

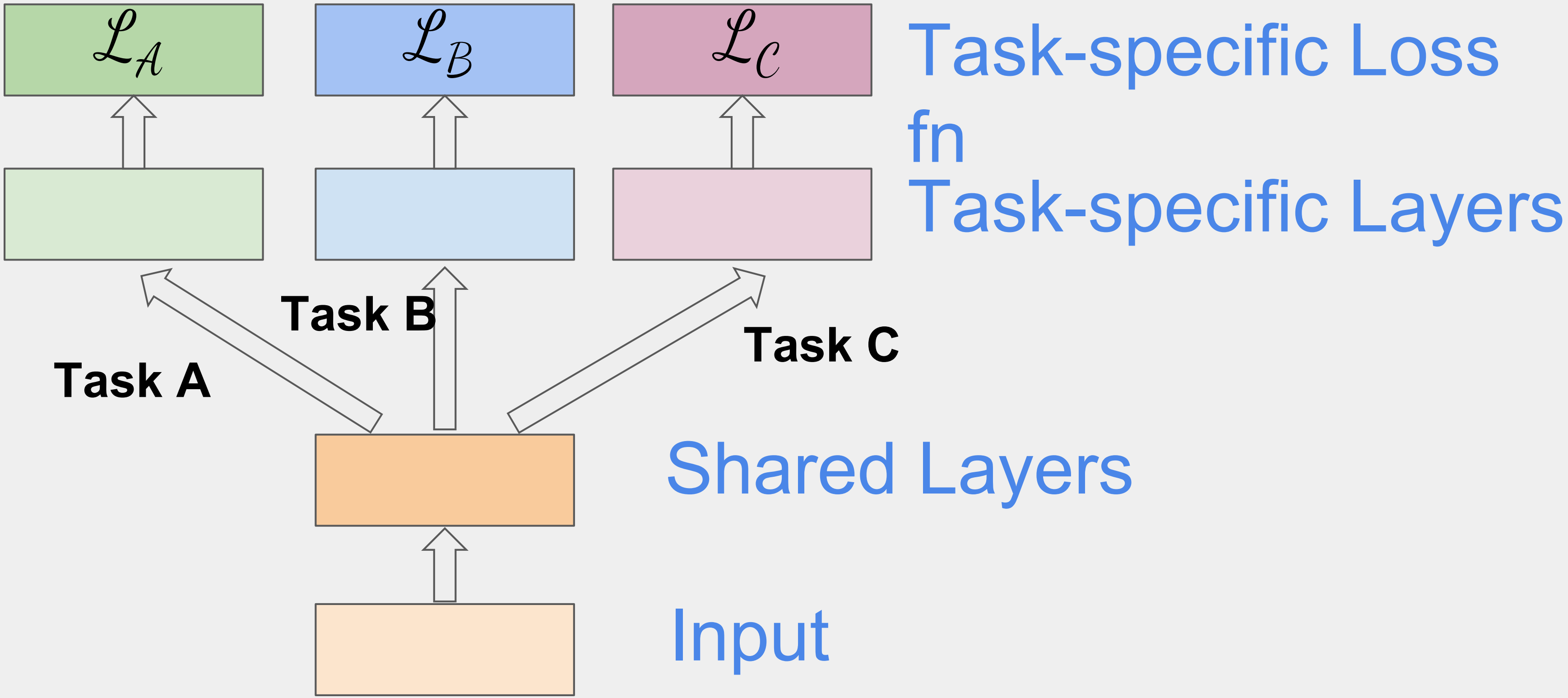
- Learning of a new tasks relies on the previous learned tasks:
  - Learning process can be faster, more accurate and/or need less training data



Traditional Learning vs Transfer Learning

via towardsdatascience.com

Multi-task learning: Classical Paradigm



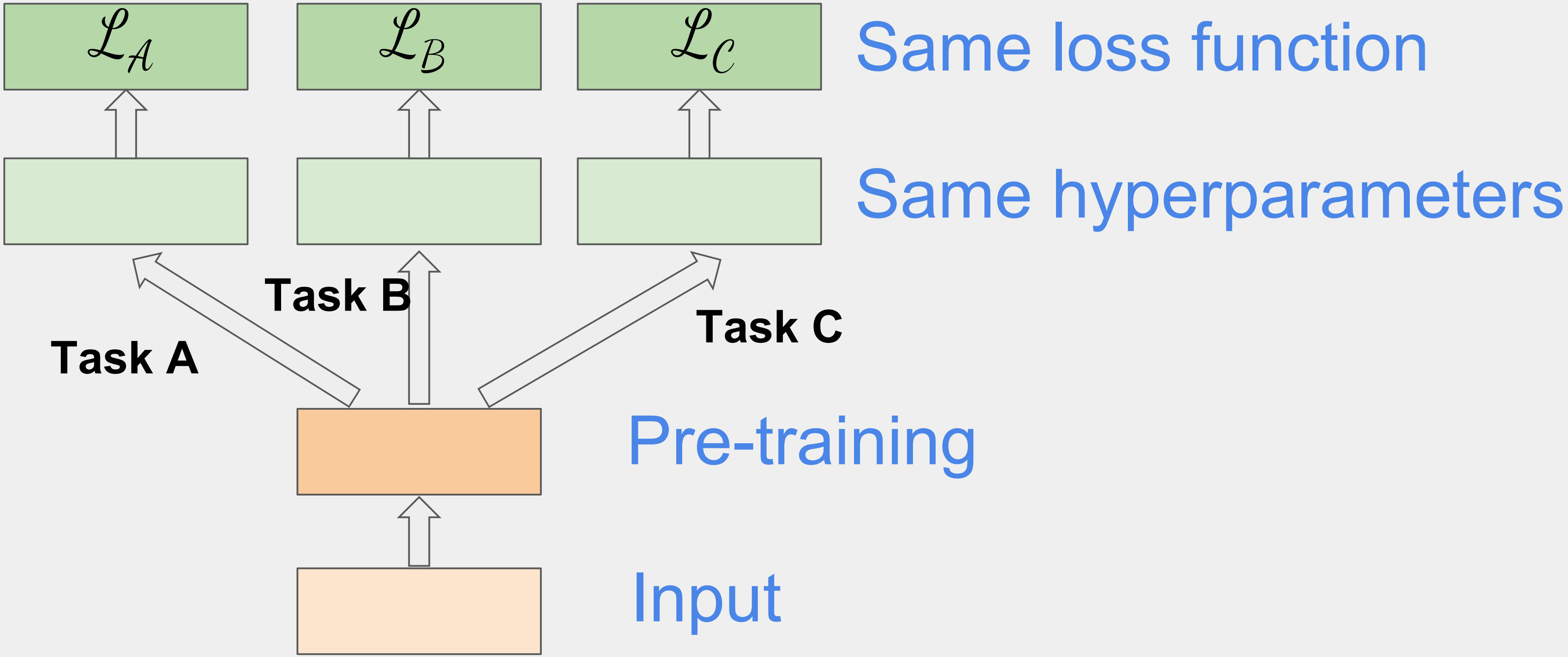
Multi-task learning: Classical Paradigm

- Task-specific loss function
- Task specific architectural layers

T5 (Text-to-Text Transfer Transformer): Idea

- Pre-train a Transformer Encoder-Decoder model on a large unlabeled web crawl text
- Pose every NLP task as text to text (McCann et al., 2018; Radford et al., 2019)
- Fine-tune separately for each downstream task (done in parallel)

Multi-task learning: T5 Paradigm



Multi-task learning: T5 Paradigm

- Cross Entropy/Max. likelihood loss for all pre-training and fine-tuning tasks
- Same hyperparameters for each task
- “Unified” vocabulary

Unified Text-to-Text view

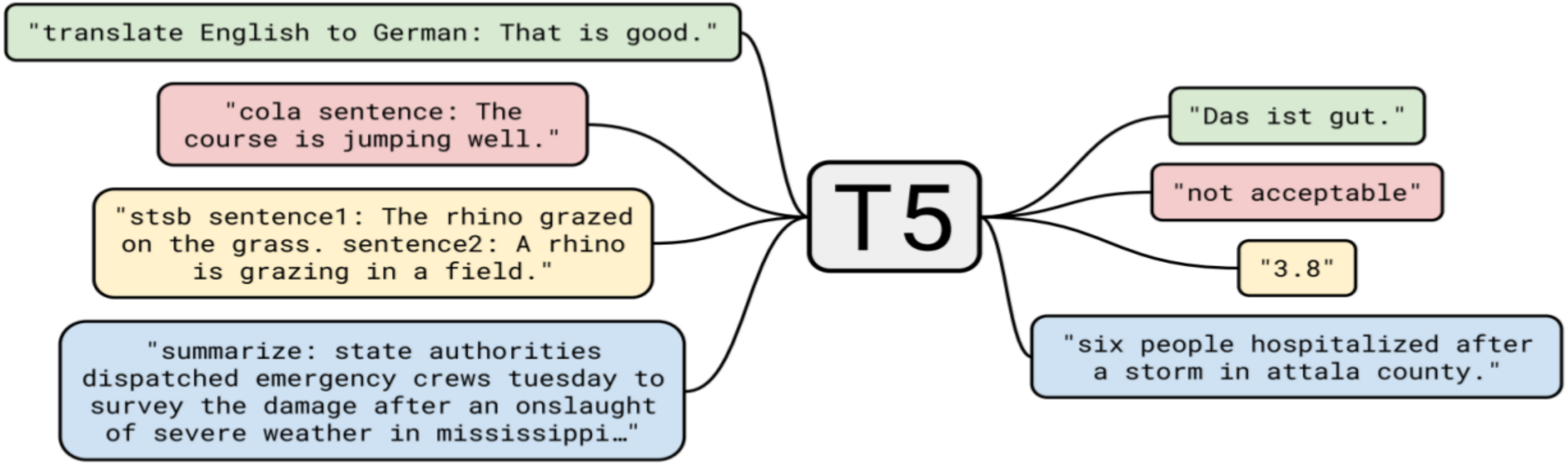


Figure 1: A diagram of our text-to-text framework. Every task we consider – including translation, question answering, and classification – is cast as feeding our model text as input and training it to generate some target text. This allows us to use the same model, loss function, hyperparameters, etc. across our diverse set of tasks. It also provides a standard testbed for the methods included in our empirical survey. "T5" refers to our model, which we dub the "**T**ext-**t**o-**T**ext **T**ransfer **T**ransformer".

Pre-training Dataset: Colossal Clean Crawled Corpus

- Goal: analyze the effect of the quality, characteristics and size of unlabeled data
- Source: https://commoncrawl.org/ (20 TB/month, noisy data)
- Data cleaning using heuristics
  - Only retain lines ending in a terminal punctuation mark (“.”, “!”, “?” etc.)
  - Remove obscene words
  - Removing pages containing Javascript code
  - Remove duplicate sentences
  - Retain only English webpages
- 750 GB

Fine-tuning (Downstream) tasks

- Text classification: GLUE and SuperGLUE
- Abstractive summarization: CNN/Daily Mail
- QA: SQuAD
- Translation: WMT English to German, French, and Romanian

Input & Output

- “text-to-text” format
- consistent training objective: maximum likelihood
- task-specific (text) prefix
- Mismatch label Issue
  - e.g. given a premise and hypothesis, classify into one of 3 categories - ‘entailment’, ‘contradiction’ and ‘neutral’
  - Potentially possible for decoder to output ‘hamburger’
  - This issue never observed with their trained models

Input & Output

- Regression task
  - Predict a score between 1 to 5
  - Convert to 21-class classification i.e. round target floating point score to nearest integer multiple of 0.2 and convert into string
  - At inference, convert the string back into floating point number

Input & Output

- Winograd Task (ambiguation)
    - Input - Highlighted ambiguous pronoun. e.g. “The city councilmen refused the demonstrators a permit because *they* feared violence .”
    - Output - the target noun. E.g. “The city councilmen”

Empirical Survey

Methodology “coordinate descent”

Baseline → Architecture → Objective →Dataset

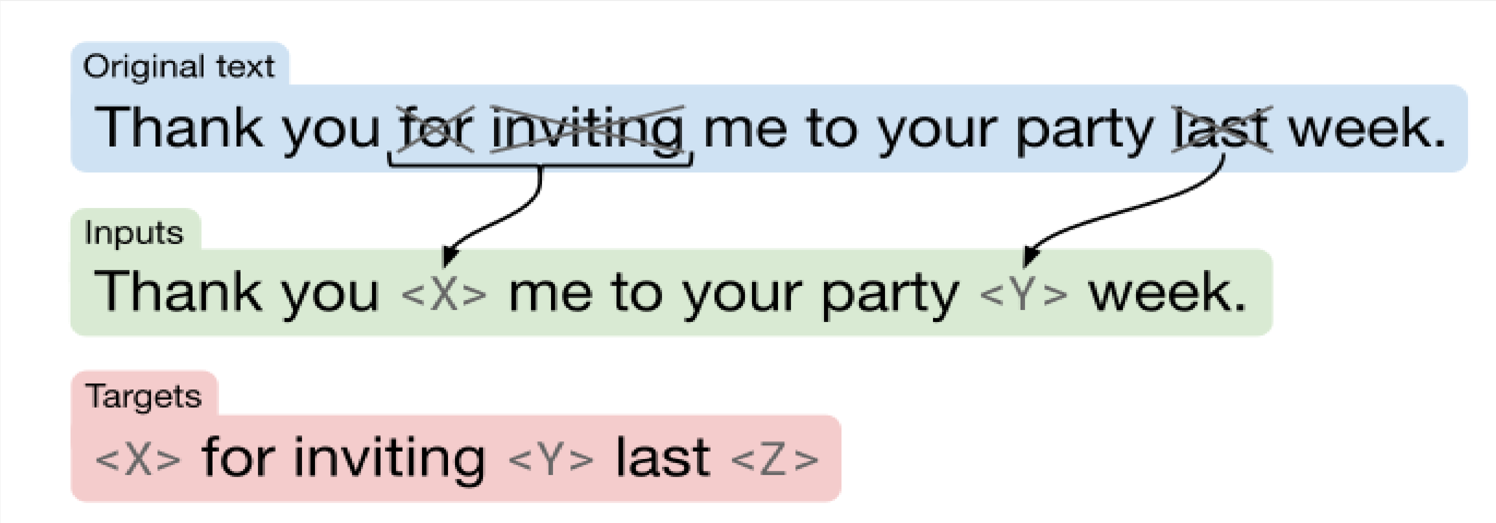
→ Transfer Approach → Scaling

Baseline

- Encoder-Decoder architecture as in original Transformer paper (Vaswani et al., 2017)
- Relative Positional self-attention (Shaw et al., 2018)
  - RelativeAttention = Softmax$\left(\frac{QK^T + S^{rel}}{\sqrt{D_h}}\right)V$
  - S^{rel} is shared across layers for a given attention head, different for different attention heads within a layer

Baseline

- Pre-training objective: Denoising(drop 15 % tokens randomly)



- BERT-base Size Encoder and Decoder (L=12, H=768, A=12)
- Multilingual Vocabulary: SentencePiece (32k word pieces)

Baseline (Pre-training Details)

- Max Sequence length: 512 tokens
- Batch size: 128 sequences = 128 × 512 = 2^{16} tokens
- Training size = 2^{19} steps = $2^{19} \times 2^{16} = 2^{35}$ tokens ≈ 34 B tokens << BERT (137B) << RoBERTa (2.2T)
- inverse square root learning rate schedule, where k = 10^4 (warm-up steps)
- AdaFactor
- Dropout: 0.1

Baseline (Fine-tuning Details)

- Batch Size: 128
- Length: 512
- Training size = 2^{18} steps = $2^{18} \times 2^{16}$ = 2^{34} tokens
- constant learning rate: 0.001
- 5,000 steps/checkpoint

Baseline Performance

	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Baseline average	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
Baseline standard deviation	0.235	0.065	0.343	0.416	0.112	0.090	0.108
No pre-training	66.22	17.60	50.31	53.04	25.86	**39.77**	24.04

Table 1: Average and standard deviation of scores achieved by our baseline model and training procedure. For comparison, we also report performance when training on each task from scratch (i.e. without any pre-training) for the same number of steps used to fine-tune the baseline model. All scores in this table (and every table in our paper except Table 14) are reported on the validation sets of each dataset.

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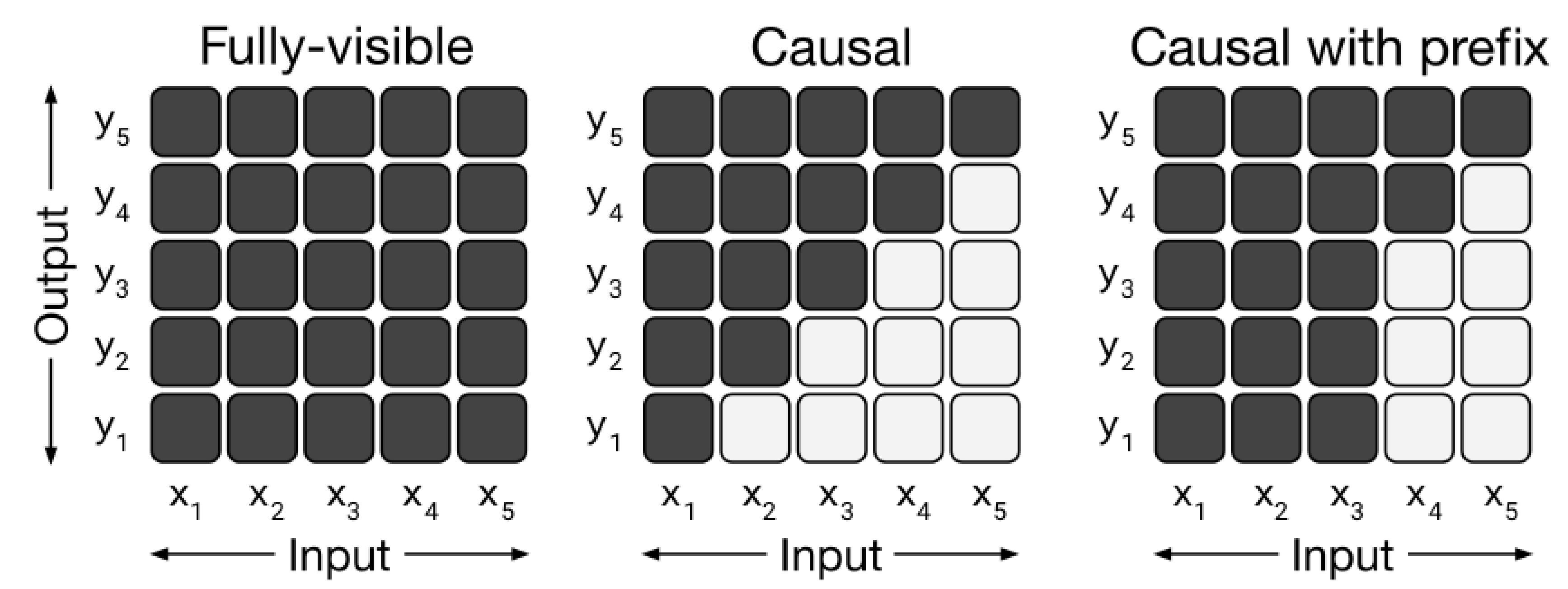
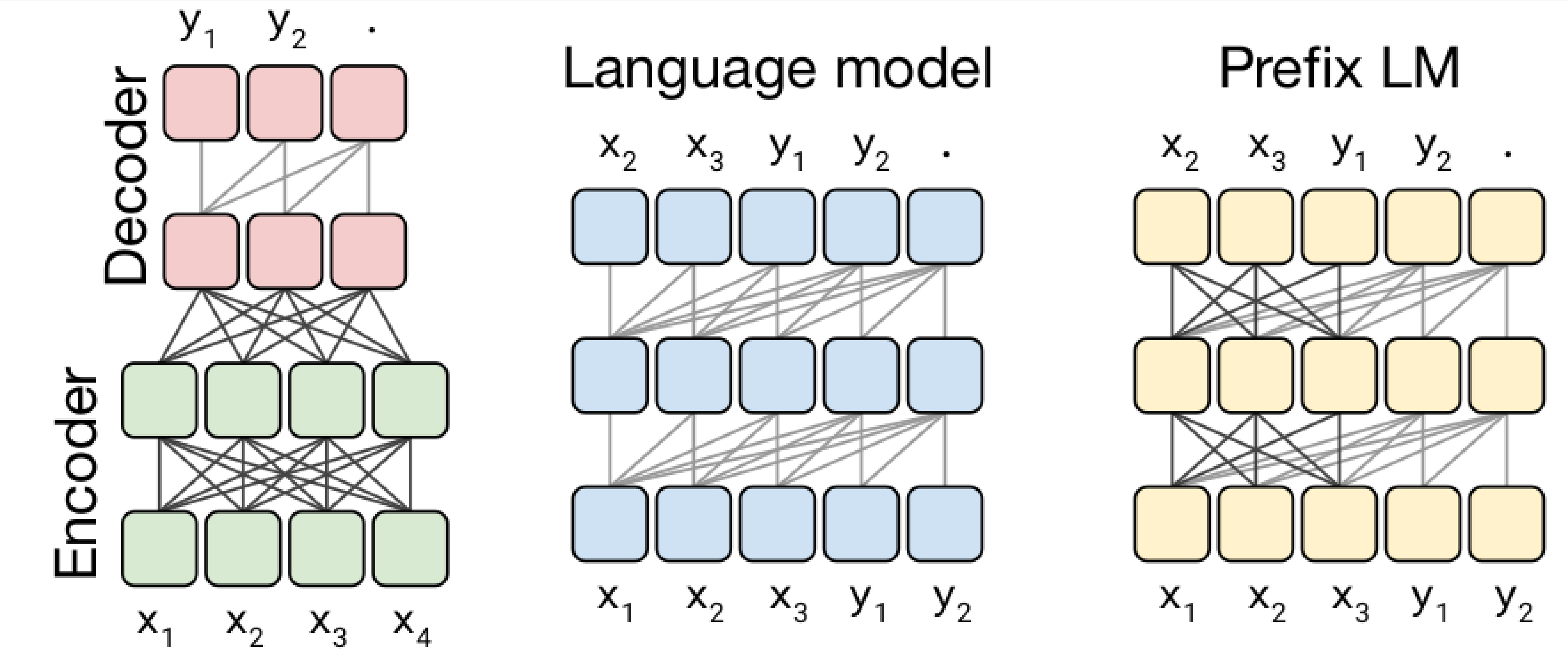
Types of Self-attention

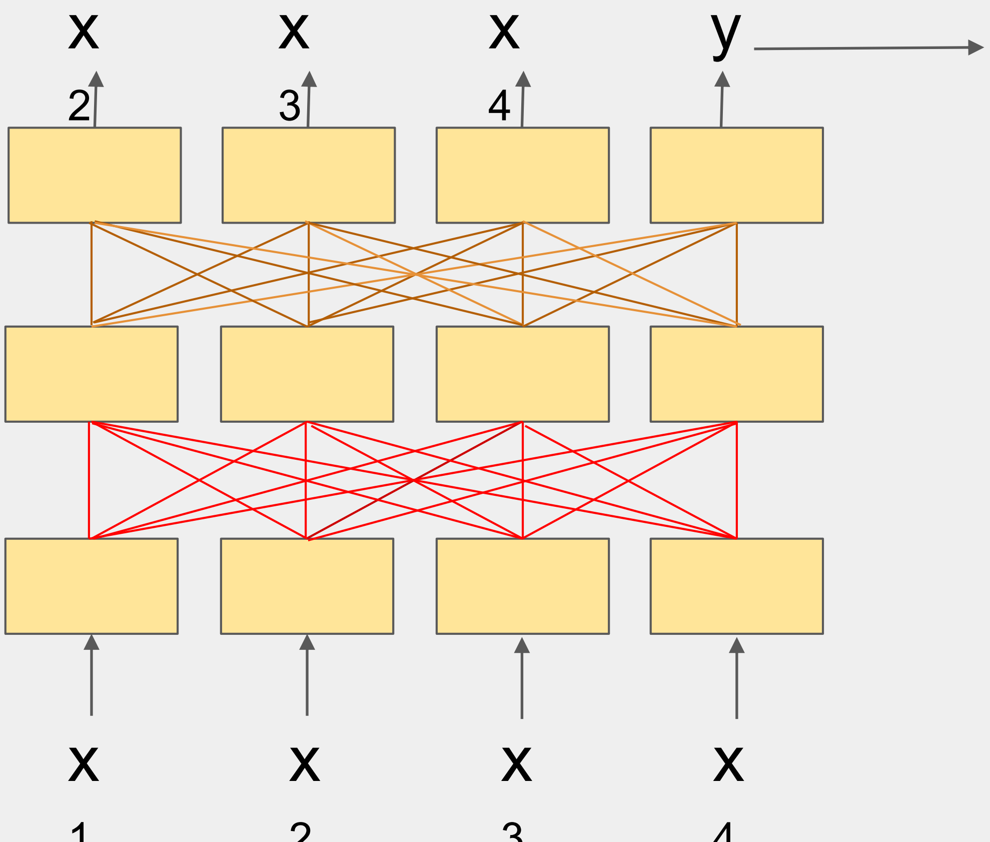


Architectural Variants



- Encoder-Decoder
  - Baseline
- Language model
  - Used in transfer learning as pre-training model with language modeling objective (Radford et al., 2018)
- Prefix LM
  - Suited for classification tasks. e.g. Input - “ mnli premise: I hate pigeons. hypothesis: My feelings towards pigeons are filled with animosity. target:”, Output - “entailment”

Prefix LM



Similar to CLS token in BERT !!!

Model Architectures: Results

Architecture	Objective	Params	Cost	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Encoder-decoder	Denoising	$2P$	M	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
Enc-dec, shared	Denoising	P	M	82.81	18.78	**80.63**	**70.73**	26.72	39.03	**27.46**
Enc-dec, 6 layers	Denoising	P	$M/2$	80.88	18.97	77.59	68.42	26.38	38.40	26.95
Language model	Denoising	P	M	74.70	17.93	61.14	55.02	25.09	35.28	25.86
Prefix LM	Denoising	P	M	81.82	18.61	78.94	68.11	26.43	37.98	27.39
Encoder-decoder	LM	$2P$	M	79.56	18.59	76.02	64.29	26.27	39.17	26.86
Enc-dec, shared	LM	P	M	79.60	18.13	76.35	63.50	26.62	39.17	27.05
Enc-dec, 6 layers	LM	P	$M/2$	78.67	18.26	75.32	64.06	26.13	38.42	26.89
Language model	LM	P	M	73.78	17.54	53.81	56.51	25.23	34.31	25.38
Prefix LM	LM	P	M	79.68	17.84	76.87	64.86	26.28	37.51	26.76

- Surprisingly, *Enc-dec shared* performs nearly as well as baseline and better than prefix LM. (**ALBERT, XLNet**)
- Explicit encoder-decoder structure can be useful
- Denoising objective > LM objective

Empirical Survey

Methodology “coordinate descent”

Baseline → Architecture → **Objective** →Dataset

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Pre-training: Bert vs Non-Bert style

Objective	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
Prefix language modeling	80.69	18.94	77.99	65.27	**26.86**	39.73	**27.49**
BERT-style [Devlin et al., 2018]	**82.96**	**19.17**	**80.65**	**69.85**	**26.78**	**40.03**	**27.41**
Deshuffling	73.17	18.59	67.61	58.47	26.11	39.30	25.62

Variants of Masked LM

Objective	Input	Output
BERT-style	15 % corruption → (90 % MASK, 10 % random tokens)	Original full text
MASS-style	15 % corruption → (100 % MASK)	Original full text
Replace corrupted spans	Thank you <X> me to your party <Y> week .	<X> for inviting <Y> last <Z>
Drop corrupted tokens	Thank you me to your party week .	for inviting last

Results

Objective	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
BERT-style [Devlin et al., 2018]	82.96	19.17	**80.65**	69.85	26.78	**40.03**	27.41
MASS-style [Song et al., 2019]	82.32	19.16	80.10	69.28	26.79	**39.89**	27.55
★ Replace corrupted spans	83.28	**19.24**	**80.88**	**71.36**	**26.98**	39.82	**27.65**
Drop corrupted tokens	**84.44**	**19.31**	**80.52**	68.67	**27.07**	39.76	**27.82**

Short Target &
Fast Training

Due to CoLA

Results

- Corruption rate:
  - Not sensitive

	Corruption rate	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
	10%	**82.82**	19.00	**80.38**	69.55	**26.87**	39.28	**27.44**
★	15%	**83.28**	19.24	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
	25%	**83.00**	**19.54**	**80.96**	70.48	**27.04**	**39.83**	**27.47**
	50%	81.27	19.32	79.80	70.33	**27.01**	**39.90**	**27.49**

Results

- token-level vs span-level corruption
  - Slight improvement with span length 3

Span length	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Baseline (i.i.d.)	**83.28**	19.24	80.88	71.36	**26.98**	**39.82**	**27.65**
2	**83.54**	19.39	**82.09**	**72.20**	**26.76**	**39.99**	**27.63**
3	**83.49**	**19.62**	**81.84**	**72.53**	**26.86**	39.65	**27.62**
5	**83.40**	19.24	**82.05**	**72.23**	**26.88**	39.40	**27.53**
10	82.85	19.33	**81.84**	70.44	**26.79**	39.49	**27.69**

Message

- Small modification to the masked language model objective may not lead to significant improvement.
- Try something different !!!

Empirical Survey

Methodology “coordinate descent”

Baseline → Architecture → Objective →**Dataset**

→ Transfer Approach → Scaling

Pre-training Datasets

- C4: Common Crawl with heuristic filterin
- Unfiltered C4: Common Crawl only use use langdetect to extract English text
- RealNews-like: omitted any non-news content in C4
- WebText-like (GPT2-like): high Reddit score webpages in C4
- Wikipedia
- Wikipedia + Toronto Books Corpus (BERT)

Pre-training Datasets

- Pre-training on in-domain unlabeled data can improve performance on downstream tasks.

Dataset	Size	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ C4	745GB	83.28	**19.24**	80.88	71.36	**26.98**	**39.82**	**27.65**
C4, unfiltered	6.1TB	81.46	19.14	78.78	68.04	26.55	39.34	27.21
RealNews-like	35GB	**83.83**	**19.23**	80.39	72.38	**26.75**	**39.90**	**27.48**
WebText-like	17GB	**84.03**	**19.31**	**81.42**	71.40	**26.80**	**39.74**	**27.59**
Wikipedia	16GB	81.85	**19.31**	81.29	68.01	**26.94**	39.69	**27.67**
Wikipedia + TBC	20GB	83.65	**19.28**	**82.08**	**73.24**	**26.77**	39.63	**27.57**

Table 8: Performance resulting from pre-training on different datasets. The first four variants are based on our new C4 dataset.

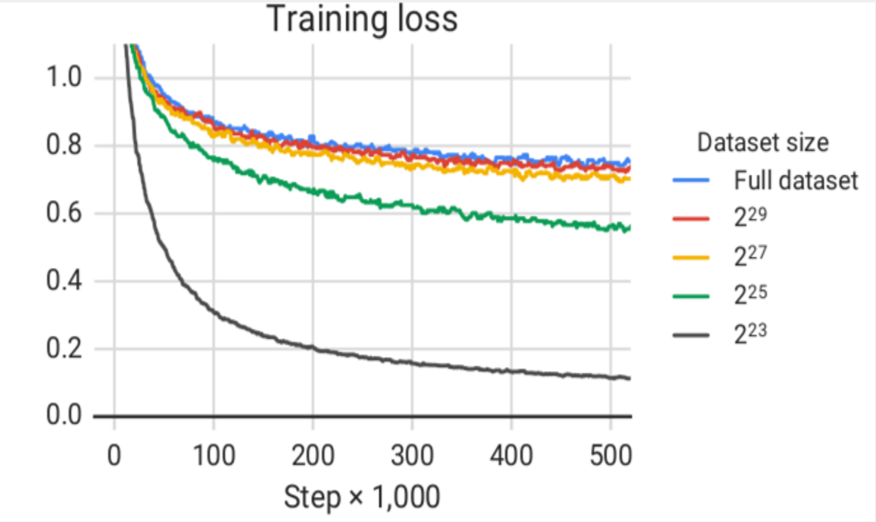
Due to ReCoRD,
News domain

Due to MultiRC,
the same domain as TBC

SQuAD, from Wikipedia

Varying No. of epochs

- Keeping total number of Training steps = constant



Number of tokens	Repeats	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Full dataset	0	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
2^{29}	64	**82.87**	**19.19**	**80.97**	**72.03**	**26.83**	**39.74**	**27.63**
2^{27}	256	82.62	**19.20**	79.78	69.97	**27.02**	**39.71**	27.33
2^{25}	1,024	79.55	18.57	76.27	64.76	26.38	39.56	26.80
2^{23}	4,096	76.34	18.33	70.92	59.29	26.37	38.84	25.81

Empirical Survey

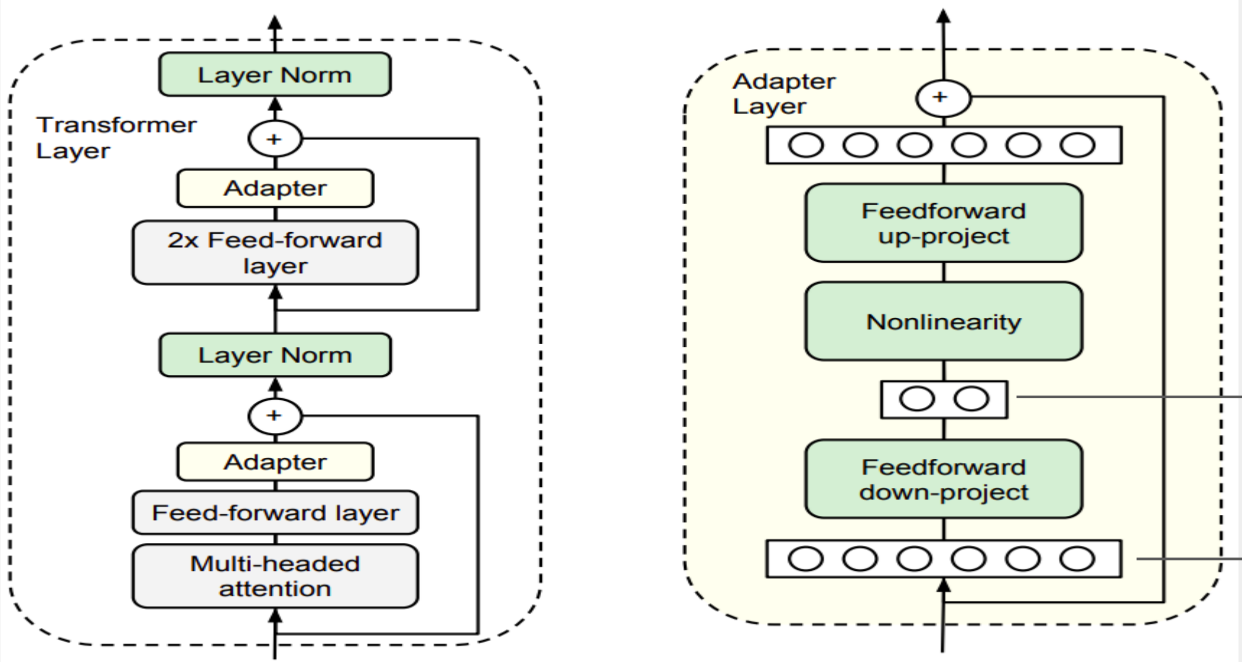
Methodology “coordinate descent”

Baseline → Architecture → Objective →Dataset

→ **Transfer Approach** → Scaling

Fine-tuning

- Adapter Layers (Houlsby et al., 2019):
  - Only adapter layers are updated



d dimensional

d_{ff} dimensional

- Gradual Unfreezing (ULMFiT):
    - First unfreeze the last layer (*which contains least general knowledge*) → the next lower layer
    - Scope for better unfreezing scheduling
- Data hungry tasks => higher value of d

Fine-tuning method	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ All parameters	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
Adapter layers, $d = 32$	80.52	15.08	79.32	60.40	13.84	17.88	15.54
Adapter layers, $d = 128$	81.51	16.62	79.47	63.03	19.83	27.50	22.63
Adapter layers, $d = 512$	81.54	17.78	79.18	64.30	23.45	33.98	25.81
Adapter layers, $d = 2048$	81.51	16.62	79.47	63.03	19.83	27.50	22.63
Gradual unfreezing	82.50	18.95	79.17	**70.79**	26.71	39.02	26.93

Multi-task learning

- Mixing datasets for all fine-tuning tasks
  - Equal mixing: $r_m \propto 1$
  - Examples-proportional mixing: $r_m \propto \min(s_m, K)$
  - Temperature scaled mixing (Multilingual BERT): $r_m \propto$

Mixing strategy	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Baseline (pre-train/fine-tine)	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
Equal	76.13	19.02	76.51	63.37	23.89	34.31	26.78
Examples-proportional, $K = 2^{16}$	80.45	19.04	77.25	69.95	24.35	34.99	27.10
Examples-proportional, $K = 2^{17}$	81.56	19.12	77.00	67.91	24.36	35.00	27.25
Examples-proportional, $K = 2^{18}$	81.67	19.07	78.17	67.94	24.57	35.19	27.39
Examples-proportional, $K = 2^{19}$	81.42	**19.24**	79.78	67.30	25.21	36.30	**27.76**
Examples-proportional, $K = 2^{20}$	80.80	**19.24**	**80.36**	67.38	25.66	36.93	**27.68**
Examples-proportional, $K = 2^{21}$	79.83	18.79	79.50	65.10	25.82	37.22	27.13
Temperature-scaled, $T = 2$	81.90	**19.28**	79.42	69.92	25.42	36.72	27.20
Temperature-scaled, $T = 4$	80.56	**19.22**	77.99	69.54	25.04	35.82	27.45
Temperature-scaled, $T = 8$	77.21	19.10	77.14	66.07	24.55	35.35	27.17

Combining multi-task learning with fine-tuning

Training strategy	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Unsupervised pre-training + fine-tuning	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	39.82	27.65
Multi-task training	81.42	**19.24**	79.78	67.30	25.21	36.30	27.76
Multi-task pre-training + fine-tuning	**83.11**	**19.12**	**80.26**	**71.03**	**27.08**	39.80	**28.07**
Leave-one-out multi-task training	81.98	19.05	79.97	**71.68**	**26.93**	39.79	**27.87**
Supervised multi-task pre-training	79.93	18.96	77.38	65.36	26.81	**40.13**	**28.04**

Empirical Survey

Methodology “coordinate descent”

Baseline → Architecture → Objective →Dataset

→ Transfer Approach → **Scaling**

- Allowed compute power = 4x
  - increasing both the training time as well as model size can be complementary
- Scaling model size: main idea to increase d_{ff} substantially
  - TPUs efficient for dense tensor multiplications

Scaling strategy	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
Baseline	83.28	19.24	80.88	71.36	26.98	39.82	27.65
1× size, 4× training steps	85.33	19.33	82.45	74.72	27.08	40.66	27.93
1× size, 4× batch size	84.60	19.42	82.52	74.64	27.07	40.60	27.84
2× size, 2× training steps	**86.18**	19.66	**84.18**	77.18	27.52	**41.03**	28.19
4× size, 1× training steps	**85.91**	19.73	**83.86**	**78.04**	27.47	40.71	28.10
4× ensembled	84.77	**20.10**	83.09	71.74	**28.05**	40.53	**28.57**
4× ensembled, fine-tune only	84.05	19.57	82.36	71.55	27.55	40.22	28.09

State-of-the-Art

Baseline → Architecture → Objective →Dataset

→ Transfer Approach → Scaling

Model

- Objective: span-corruption (SpanBERT) with span length 3
- Longer training: 1M steps with batch size 2048 → 1T tokens
  - 8x BERT, 2x XLNet, ½ x RoBERTa
- Model sizes:
  - Small: 60M Base: 220M Large: 770M XLarge: 3B XXLarge: 11B
- Multi-task pre-training (MT-DNN):
  - Monitor downstream task performance while pre-training
- Finetune on GLUE and SuperGLUE: 8 batch size

Model	GLUE Average	CoLA Matthew's	SST-2 Accuracy	MRPC F1	MRPC Accuracy	STS-B Pearson	STS-B Spearman
Previous best	89.4[a]	69.2[b]	**97.1**[a]	**93.6**[b]	**91.5**[b]	**92.7**[b]	**92.3**[b]
T5-Small	77.4	41.0	91.8	89.7	86.6	85.6	85.0
T5-Base	82.7	51.1	95.2	90.7	87.5	89.4	88.6
T5-Large	86.4	61.2	96.3	92.4	89.9	89.9	89.2
T5-3B	88.5	67.1	97.4	92.5	90.0	90.6	89.8
T5-11B	**89.7**	**70.8**	**97.1**	91.9	89.2	92.5	92.1

Model	QQP F1	QQP Accuracy	MNLI-m Accuracy	MNLI-mm Accuracy	QNLI Accuracy	RTE Accuracy	WNLI Accuracy
Previous best	**74.8**[c]	**90.7**[b]	91.3[a]	91.0[a]	**99.2**[a]	89.2[a]	91.8[a]
T5-Small	70.0	88.0	82.4	82.3	90.3	69.9	69.2
T5-Base	72.6	89.4	87.1	86.2	93.7	80.1	78.8
T5-Large	73.9	89.9	89.9	89.6	94.8	87.2	85.6
T5-3B	74.4	89.7	91.4	91.2	96.3	91.1	89.7
T5-11B	74.6	90.4	**92.0**	**91.7**	96.7	**92.5**	**93.2**

Model	SQuAD EM	SQuAD F1	SuperGLUE Average	BoolQ Accuracy	CB F1	CB Accuracy	COPA Accuracy
Previous best	88.95[d]	94.52[d]	84.6[e]	87.1[e]	90.5[e]	95.2[e]	90.6[e]
T5-Small	79.10	87.24	63.3	76.4	56.9	81.6	46.0
T5-Base	85.44	92.08	76.2	81.4	86.2	94.0	71.2
T5-Large	86.66	93.79	82.3	85.4	91.6	94.8	83.4
T5-3B	88.53	94.95	86.4	89.9	90.3	94.4	92.0
T5-11B	**90.06**	**95.64**	**88.9**	**91.0**	**93.0**	**96.4**	**94.8**

Model	MultiRC F1a	MultiRC EM	ReCoRD F1	ReCoRD Accuracy	RTE Accuracy	WiC Accuracy	WSC Accuracy
Previous best	84.4[e]	52.5[e]	90.6[e]	90.0[e]	88.2[e]	69.9[e]	89.0[e]
T5-Small	69.3	26.3	56.3	55.4	73.3	66.9	70.5
T5-Base	79.7	43.1	75.0	74.2	81.5	68.3	80.8
T5-Large	83.3	50.7	86.8	85.9	87.8	69.3	86.3
T5-3B	86.8	58.3	91.2	90.4	90.7	72.1	90.4
T5-11B	**88.2**	**62.3**	**93.3**	**92.5**	**92.5**	**76.1**	**93.8**

Model	WMT EnDe BLEU	WMT EnFr BLEU	WMT EnRo BLEU	CNN/DM ROUGE-1	CNN/DM ROUGE-2	CNN/DM ROUGE-L
Previous best	**33.8**[f]	**43.8**[f]	**38.5**[g]	43.47[h]	20.30[h]	40.63[h]
T5-Small	26.7	36.0	26.8	41.12	19.56	38.35
T5-Base	30.9	41.2	28.0	42.05	20.34	39.40
T5-Large	32.0	41.5	28.1	42.50	20.68	39.75
T5-3B	31.8	42.6	28.2	42.72	21.02	39.94
T5-11B	32.1	43.4	28.1	**43.52**	**21.55**	**40.69**

Takeaways

- Text-to-text framework comparable to task-specific architectures
- Original Encoder-Decoder ≈ shared Encoder-Decoder
- Denoising objectives > LM objective
- Pre-training on in-domain unlabeled data useful for a few downstream tasks
- Scaling could be most useful when both model size and training steps are increased
- Pushing limits (11 B parameters) on transformer-like architectures can help achieve SOTA

Cons

- Not language-agnostic (Atishya, Sankalan, Pratyush, Soumya, Jigyasa)
- Large carbon footprints (Keshav, Rajas, Saransh)
- Saturation point of size still not known (Jigyasa)
- Not much different from BERT (Siddhant, Rajas)
- Better data cleaning heuristics (Pratyush, Keshav)

Possible extensions

- Extending to Graphs (KBs) [Keshav, Atishya]
    - Leverage OpenIE to construct graphs with clustering of related paragraphs
    - Pre-training task: Predict a sentence from the graph given its neighbouring ones
    - Leverage Graph transformers (Yun et al., 2019) for fine-tuning
- Alternatives to Gradual unfreezing [Rajas, Saransh]
    - RL based approach
- Balance scalability vs Performance trade-off in practical settings [Shubham, Lovish]

Possible extensions

- Multi-lingual learning [Pratyush, Sankalan]
  - Lakew et al., 2018

Thank You !!!