What can MIR learn from transfer learning in NLP?

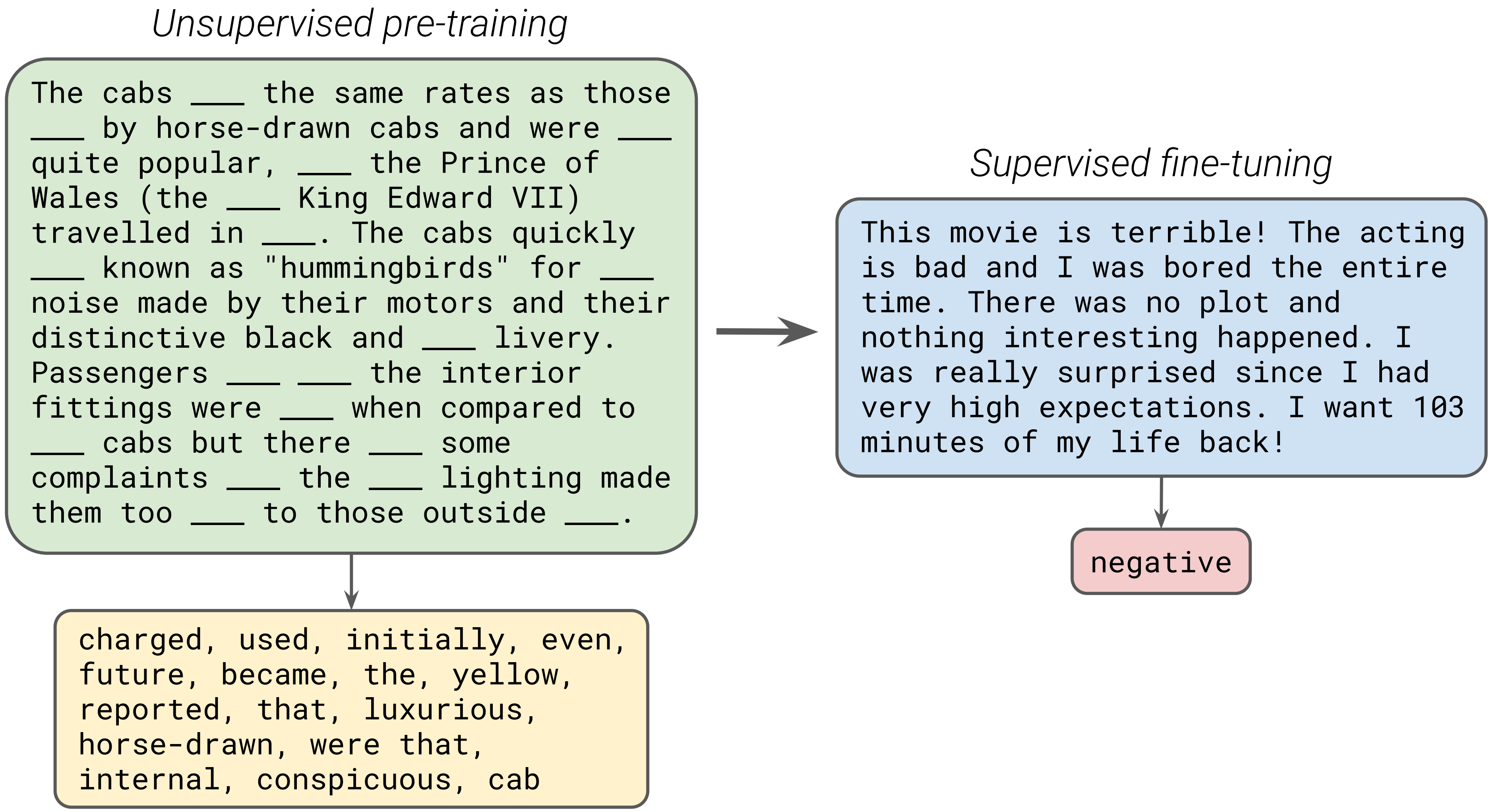
Colin Raffel

NLP4MusA (*First Workshop on NLP for Music and Audio*)

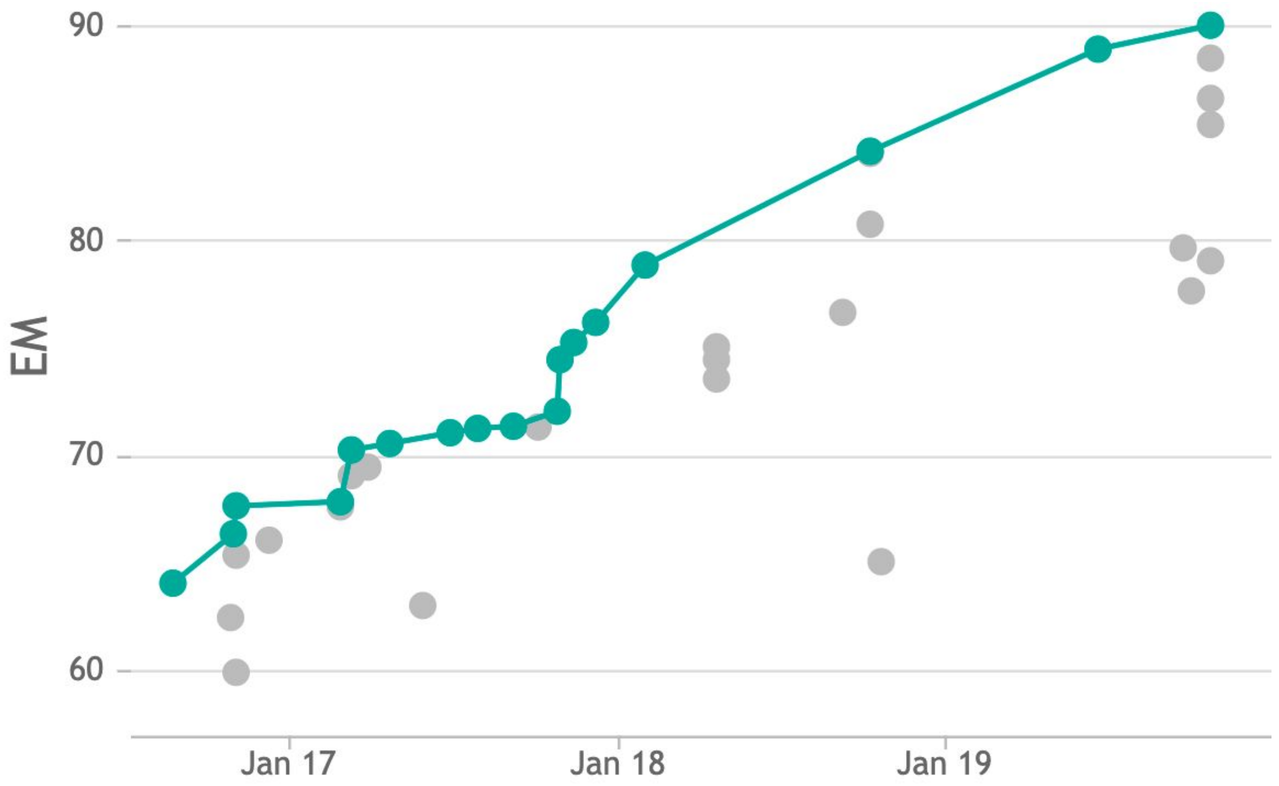
What is transfer learning and what makes it so useful?

How should we do transfer learning in NLP?

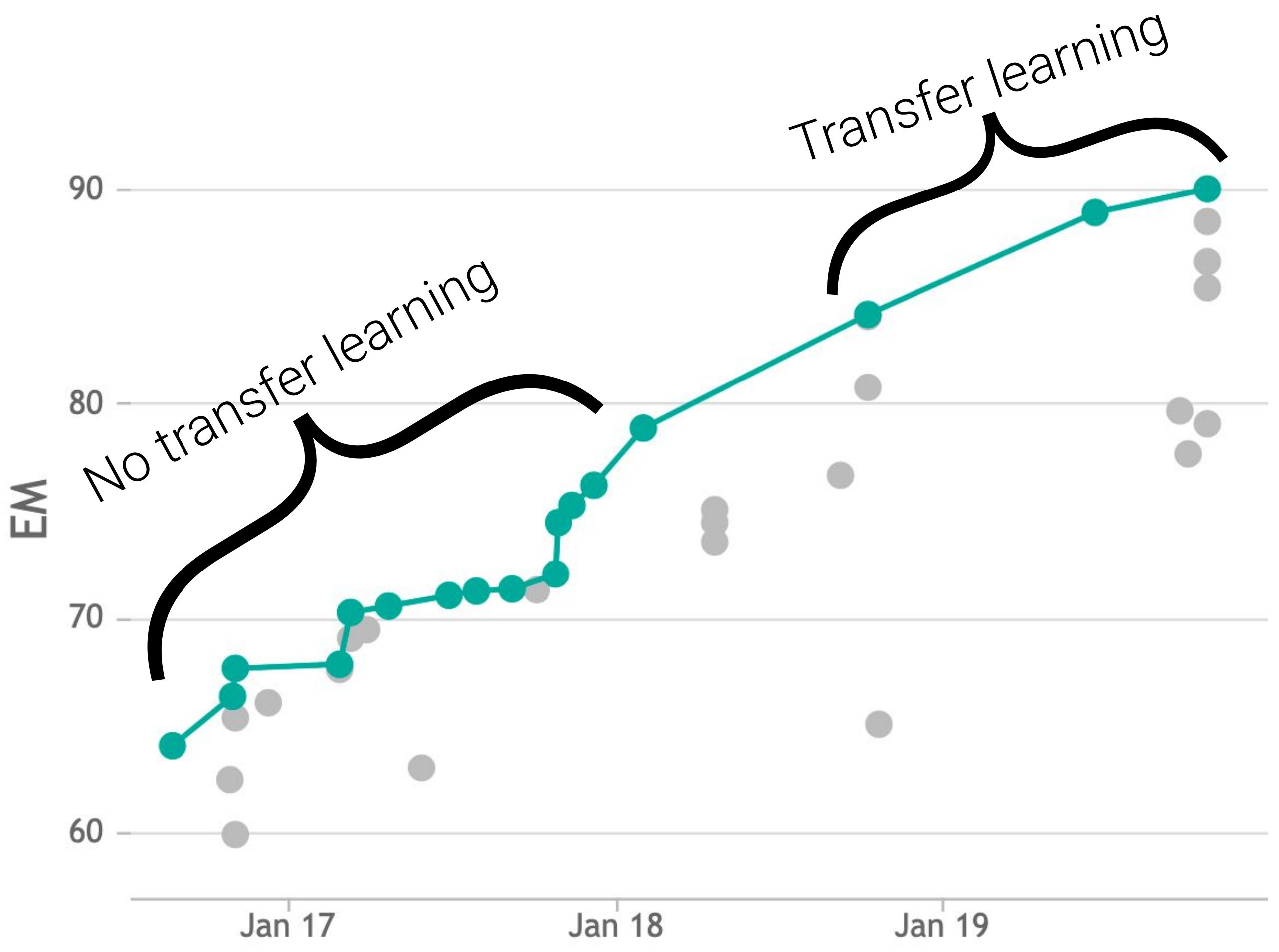
How can we apply these ideas to MIR?


Unsupervised pre-training
The cabs ___ the same rates as those ___ by horse-drawn cabs and were ___ quite popular, ___ the Prince of Wales (the ___ King Edward VII) travelled in ___. The cabs quickly ___ known as "hummingbirds" for ___ noise made by their motors and their distinctive black and ___ livery. Passengers ___ ___ the interior fittings were ___ when compared to ___ cabs but there ___ some complaints ___ the ___ lighting made them too ___ to those outside ___.
charged, used, initially, even, future, became, the, yellow, reported, that, luxurious, horse-drawn, were that, internal, conspicuous, cab
Supervised fine-tuning
This movie is terrible! The acting is bad and I was bored the entire time. There was no plot and nothing interesting happened. I was really surprised since I had very high expectations. I want 103 minutes of my life back!
negative

SQuAD Exact Match score (validation set)



Source: https://paperswithcode.com/sota/question-answering-on-squad11-dev



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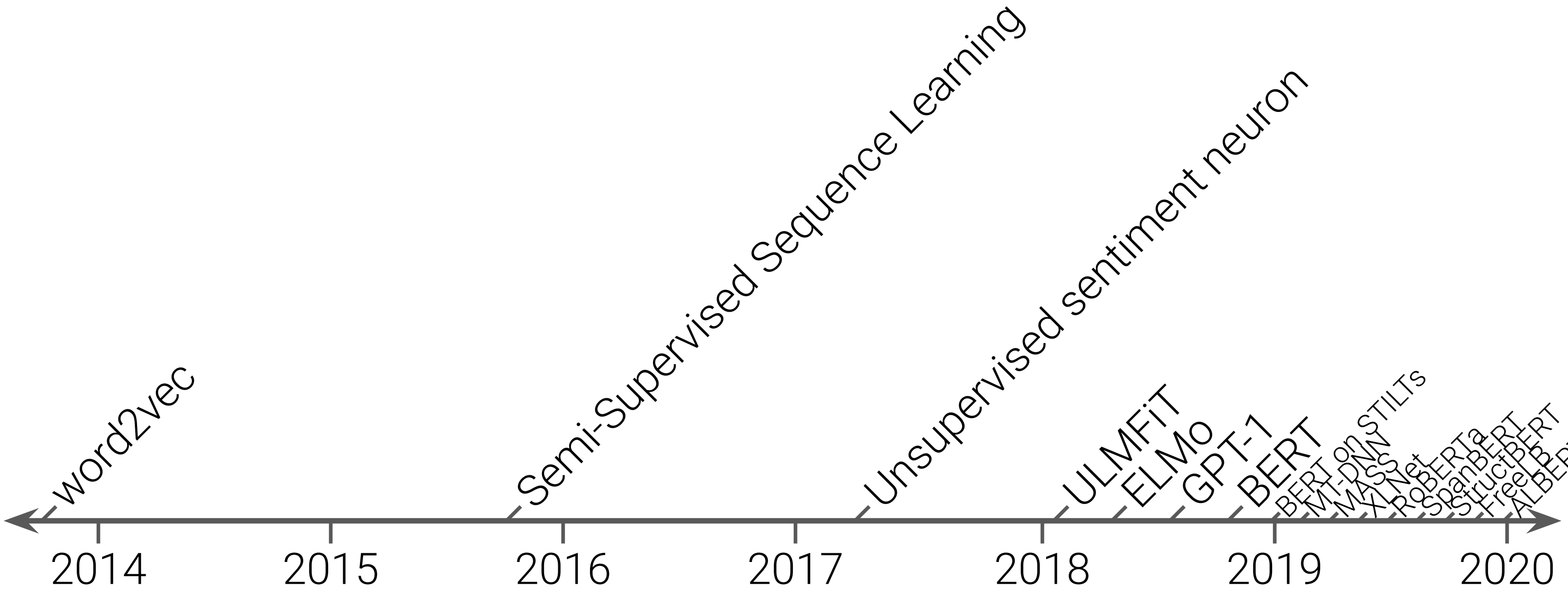
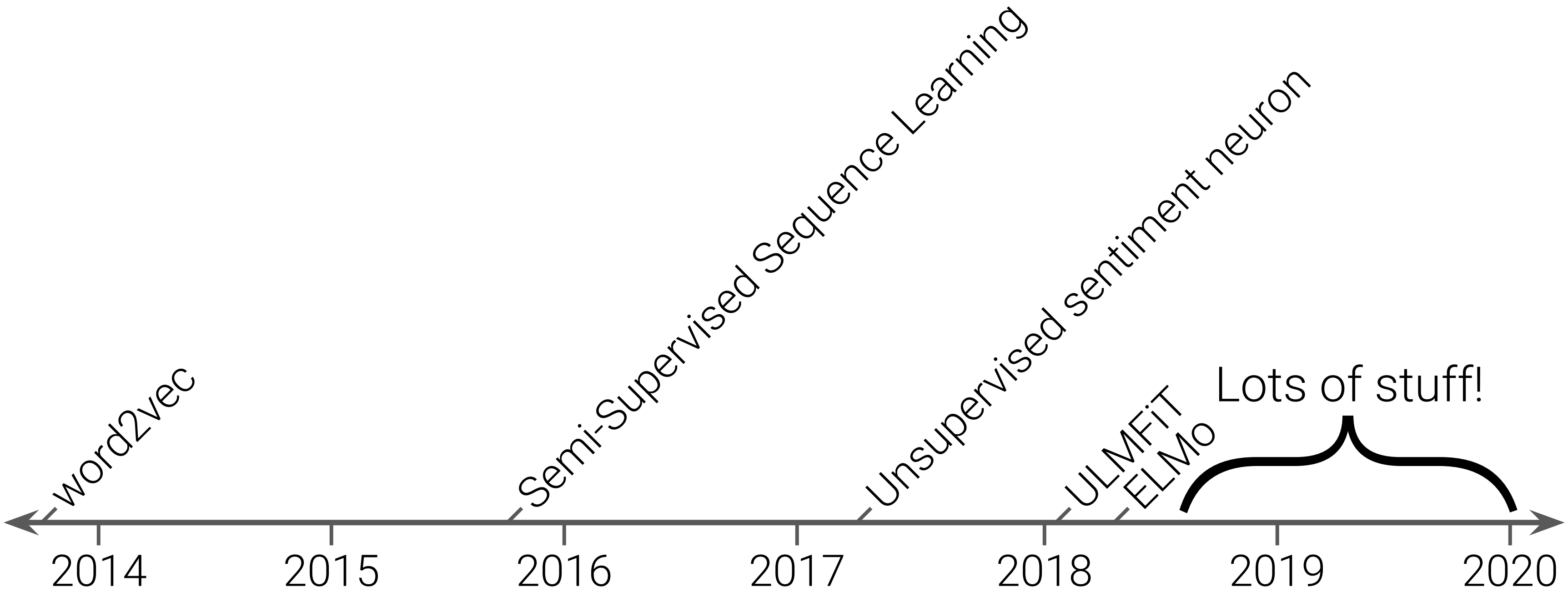
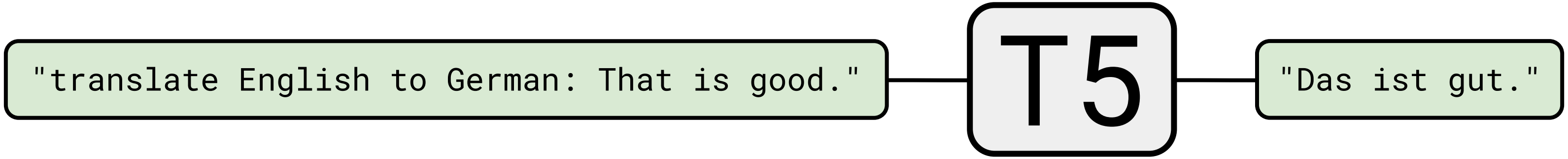


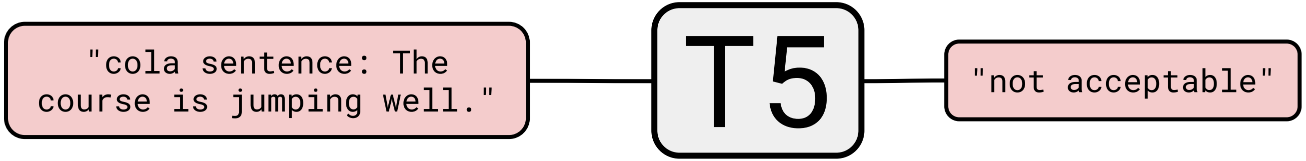
word2vec
Semi-Supervised Sequence Learning
Unsupervised sentiment neuron
ULMFiT
ELMo
GPT-1
BERT
BERT on STILTs
MT-DNN
MASS
XLNet
RoBERTa
SpanBERT
StructBERT
FreeLB
ALBERT
2014
2015
2016
2017
2018
2019
2020

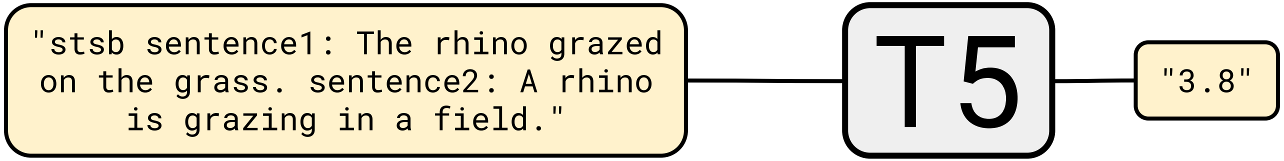

word2vec
Semi-Supervised Sequence Learning
Unsupervised sentiment neuron
ULMFiT
ELMo
Lots of stuff!
2014
2015
2016
2017
2018
2019
2020

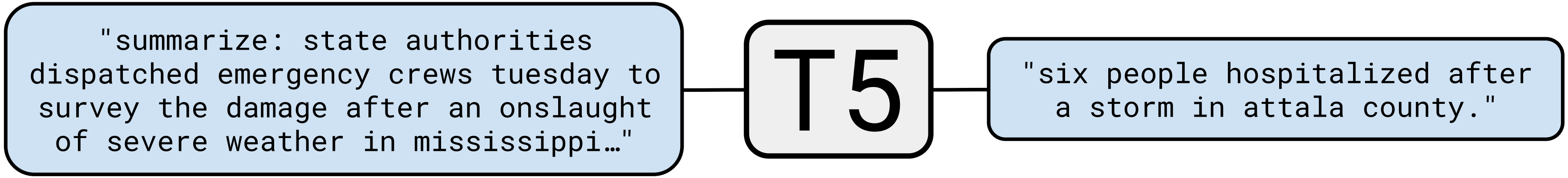
***T**ext-**t**o-**T**ext*
***T**ransfer*
***T**ransformer*

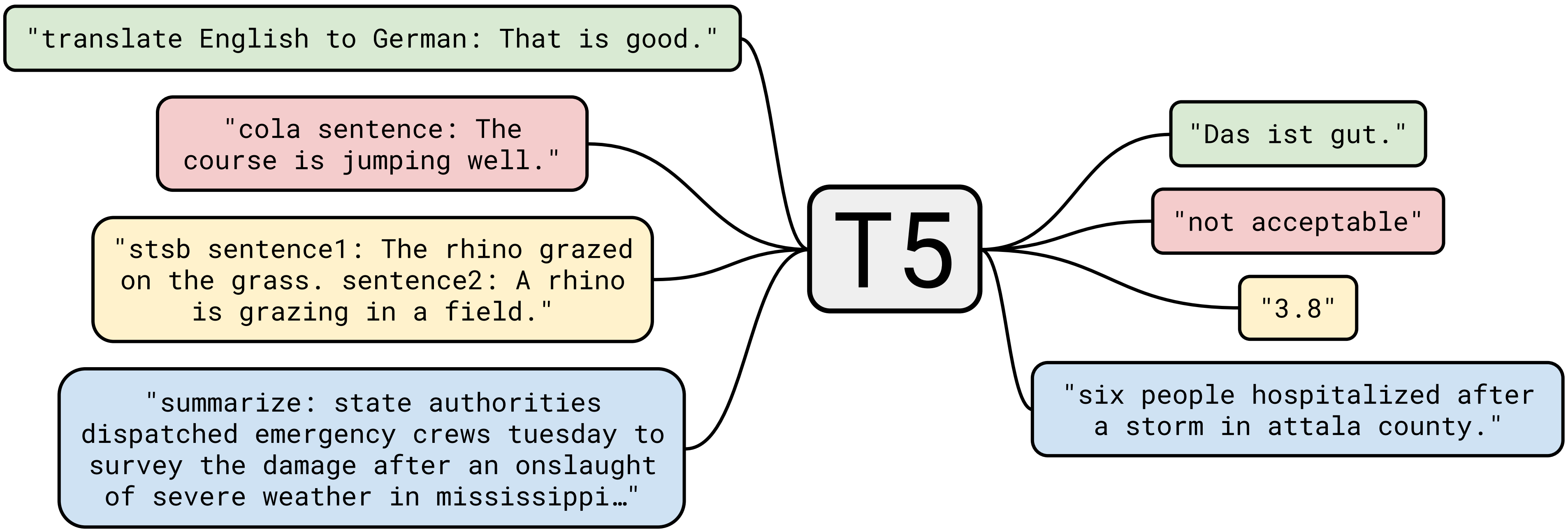
T5


"translate English to German: That is good."
T5
"Das ist gut."


"cola sentence: The course is jumping well."
T5
"not acceptable"


"stsb sentence1: The rhino grazed on the grass. sentence2: A rhino is grazing in a field."
T5
"3.8"


"summarize: state authorities dispatched emergency crews tuesday to survey the damage after an onslaught of severe weather in mississippi…"
T5
"six people hospitalized after a storm in attala county."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"summarize: state authorities dispatched emergency crews tuesday to survey the damage after an onslaught of severe weather in mississippi…"
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"Das ist gut."
"not acceptable"
"3.8"
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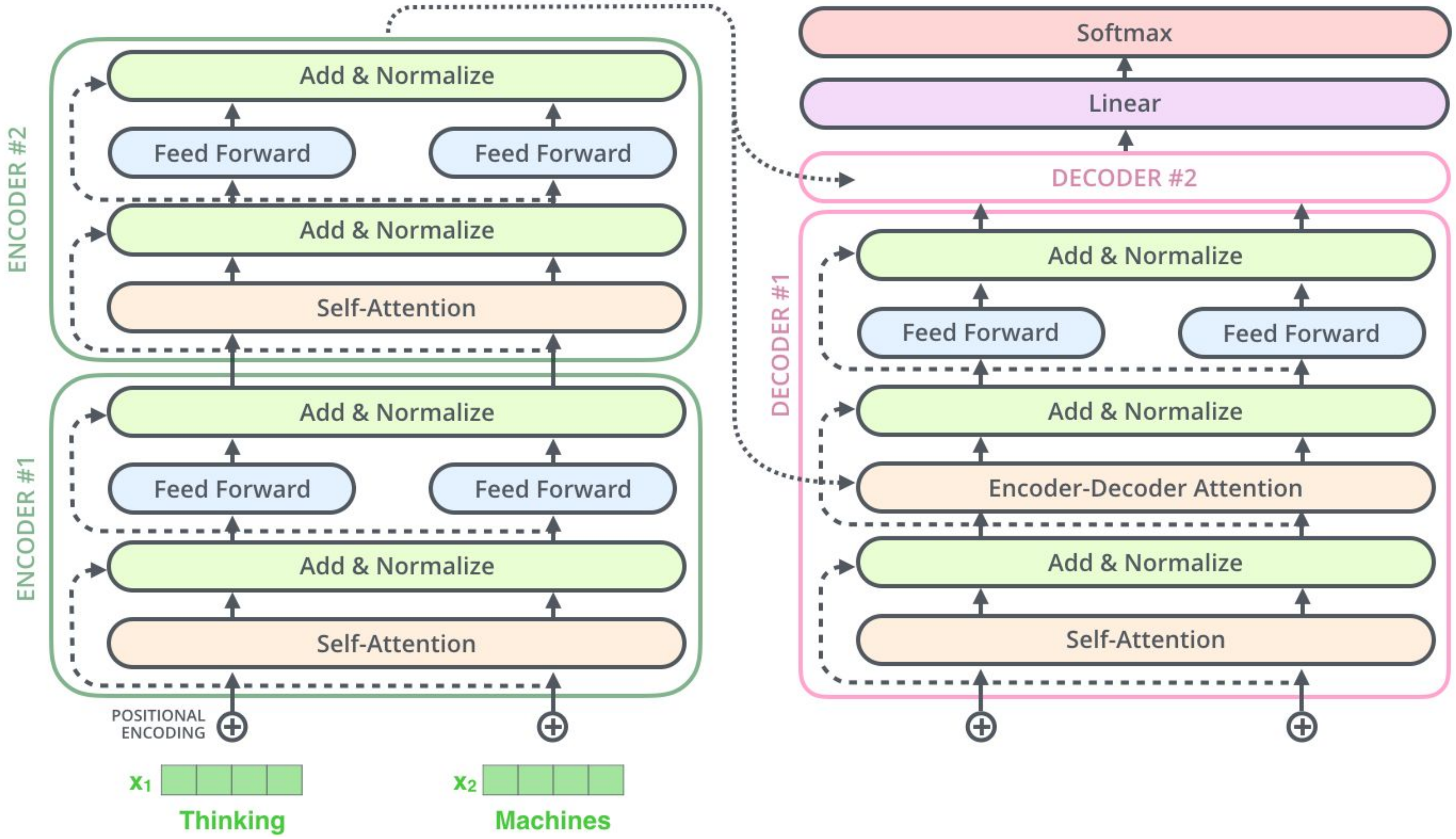

Source: http://jalammar.github.io/illustrated-transformer/

the signing of the treaty formally ended the seven years' war, known as the french and indian war in the north american theatre,[1] and marked the beginning of an era of british dominance outside europe.[2] great britain and france each returned much of the territory that they had captured during the war, but great britain gained much of france's possessions in north america. additionally, great britain agreed to protect roman catholicism in the new world...

the show has become popular in asia, and has gained online hallyu fans, having been fansubbed into various languages, such as english, spanish, portuguese, french, italian, thai, vietnamese, chinese, ...

operator, so enabling the convenient carriage of heavier and bulkier loads than would be possible were the weight carried entirely by the operator. as such it is a second-class lever...

== piano

the piano is an acoustic, stringed musical instrument invented in italy by bartolomeo cristofori around the year 1700 (the exact year is uncertain), in which the strings are struck by hammers. it is played using a keyboard,[1] which is a row of keys (small levers) that the performer presses down or strikes with the fingers and thumbs of both hands to cause the hammers to strike the strings.

the word piano is a shortened form of pianoforte, the italian term for the early 1700s versions of the instrument, which in turn derives from gravicembalo col piano e forte[2] and fortepiano. the italian musical terms piano and forte indicate

== lemon

== wheelbarrow

a wheelbarrow is a small hand-propelled vehicle, usually with just one wheel, designed to be pushed and guided by a single person using two handles at the rear, or by a sail to push the ancient wheelbarrow by wind. the term "wheelbarrow" is made of two words: "wheel" and "barrow." "barrow" is a derivation of the old english "bearwe" which was a device used for carrying loads.

Common Crawl Web Extracted Text

Menu

Lemon

Introduction

The lemon, Citrus Limon (l.) Osbeck, is a species of small evergreen tree in the flowering plant family rutaceae.
The tree's ellipsoidal yellow fruit is used for culinary and non-culinary purposes throughout the world, primarily for its juice, which has both culinary and cleaning uses.
The juice of the lemon is about 5% to 6% citric acid, with a ph of around 2.2, giving it a sour taste.

Article

The origin of the lemon is unknown, though lemons are thought to have first grown in Assam (a region in northeast India), northern Burma or China.
A genomic study of the lemon indicated it was a hybrid between bitter orange (sour orange) and citron.

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FAQ

Dried Lemons, $3.59/pound

Organic dried lemons from our farm in California.
Lemons are harvested and sun-dried for maximum flavor.
Good in soups and on popcorn.

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Lorem ipsum dolor sit amet, consectetur adipiscing elit.
Curabitur in tempus quam. In mollis et ante at consectetur.
Aliquam erat volutpat.
Donec at lacinia est.
Duis semper, magna tempor interdum suscipit, ante elit molestie urna, eget efficitur risus nunc ac elit.
Fusce quis blandit lectus.
Mauris at mauris a turpis tristique lacinia at nec ante.
Aenean in scelerisque tellus, a efficitur ipsum.
Integer justo enim, ornare vitae sem non, mollis fermentum lectus.
Mauris ultrices nisl at libero porta sodales in ac orci.

```
function Ball(r) {
   this.radius = r;
   this.area = pi * r ** 2;
   this.show = function(){
      drawCircle(r);
   }
}
```

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Lorem ipsum dolor sit amet, consectetur adipiscing elit.
Curabitur in tempus quam. In mollis et ante at consectetur.
Aliquam erat volutpat.
Donec at lacinia est.
Duis semper, magna tempor interdum suscipit, ante elit molestie urna, eget efficitur risus nunc ac elit.
Fusce quis blandit lectus.
Mauris at mauris a turpis tristique lacinia at nec ante.
Aenean in scelerisque tellus, a efficitur ipsum.
Integer justo enim, ornare vitae sem non, mollis fermentum lectus.
Mauris ultrices nisl at libero porta sodales in ac orci.

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Overview
Audio
Image
Object_detection
Structured
Summarization
Text
c4 (manual)
civil_comments
definite_pronoun_resolution
esnli
gap
glue
imdb_reviews

c4 (Manual download)

Contents

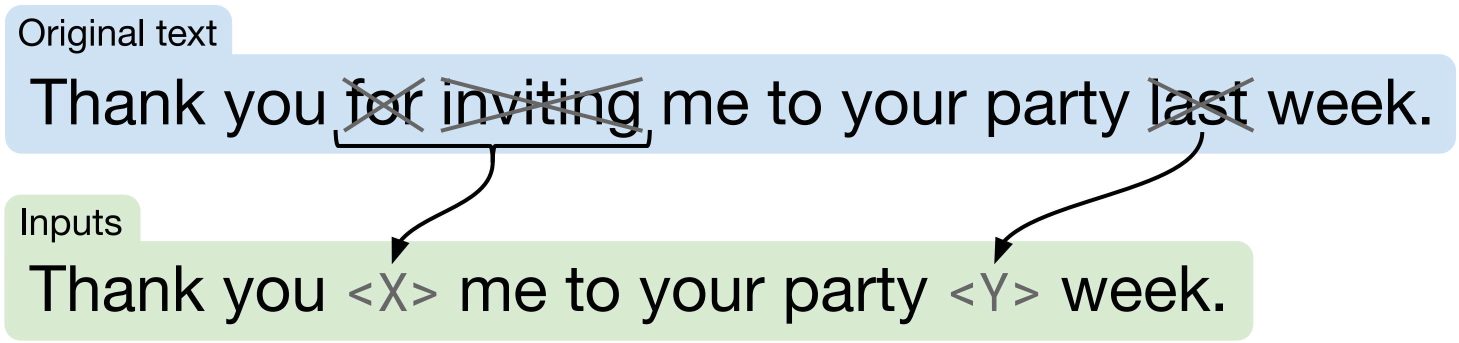
A colossal, cleaned version of Common Crawl's web crawl corpus.

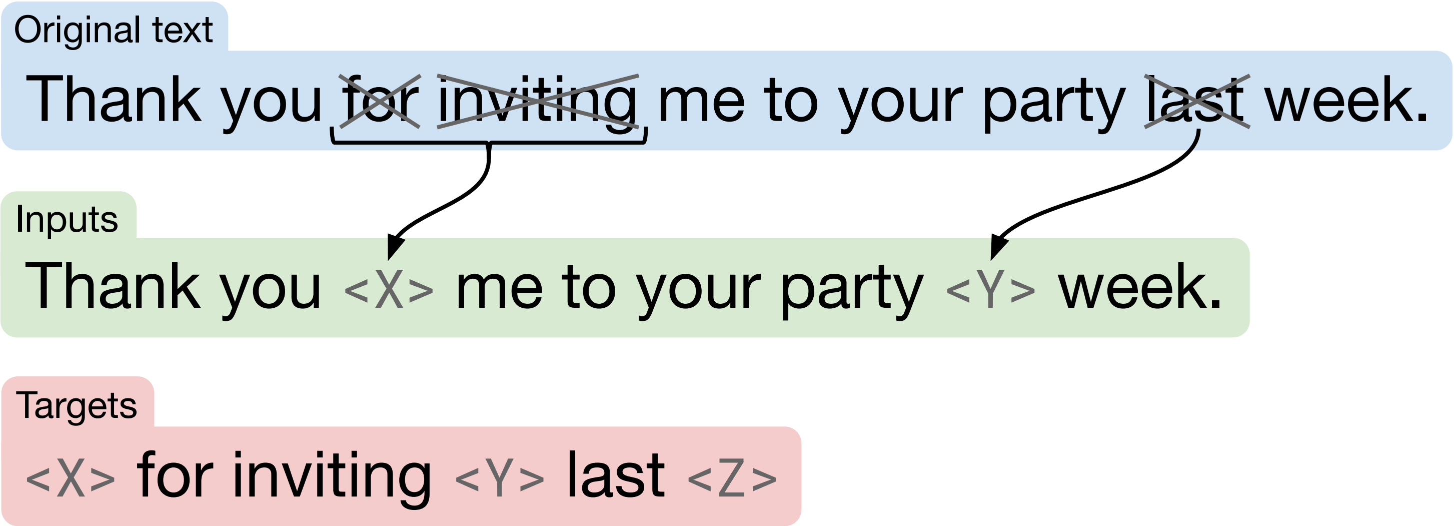
Original text

Thank you for inviting me to your party last week.

Original text

Thank you ~~for~~ ~~inviting~~ me to your party ~~last~~ week.


Original text
Thank you ~~for~~ ~~inviting~~ me to your party ~~last~~ week.
Inputs
Thank you <X> me to your party <Y> week.


Original text
Thank you ~~for~~ ~~inviting~~ me to your party ~~last~~ week.
Inputs
Thank you <X> me to your party <Y> week.
Targets
<X> for inviting <Y> last <Z>

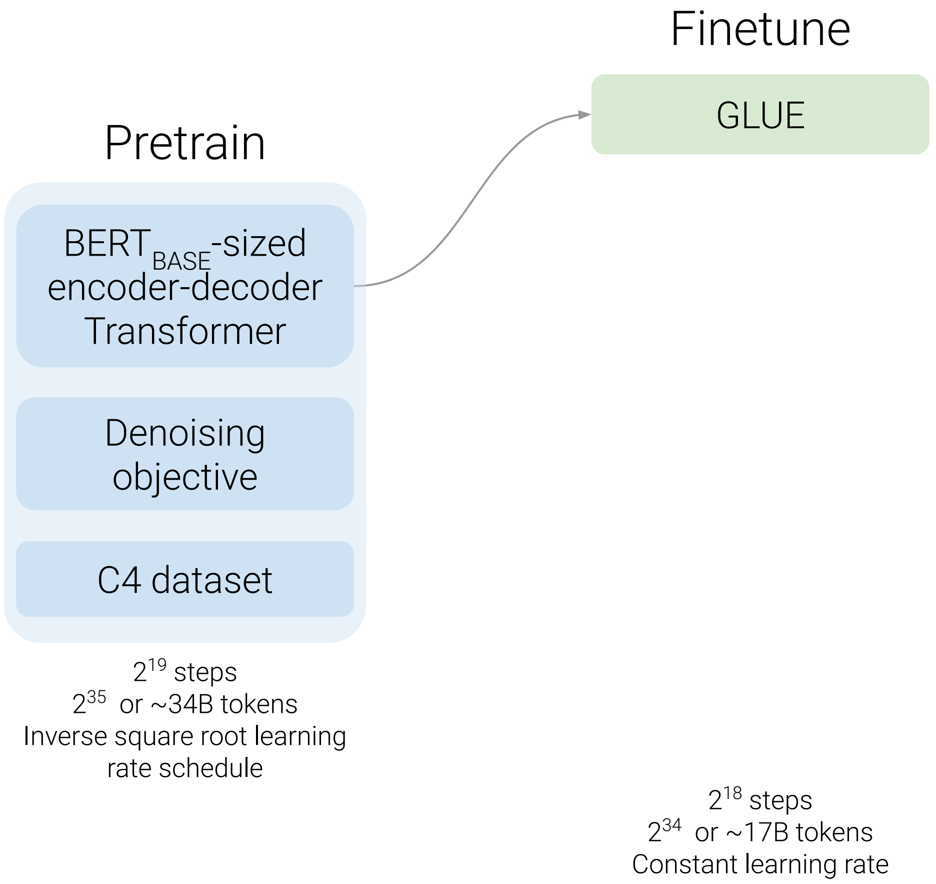
Pretrain

BERT$_{BASE}$-sized encoder-decoder Transformer

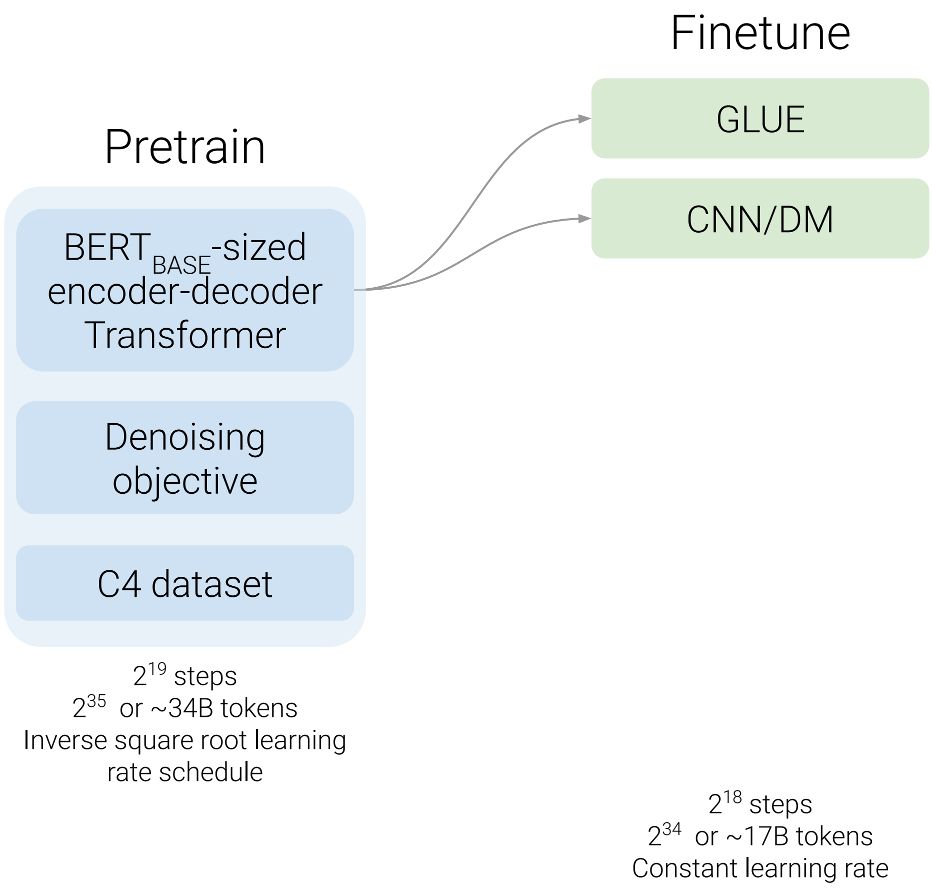
Denoising objective

C4 dataset

2^{19} steps
2^{35} or ~34B tokens
Inverse square root learning rate schedule



Finetune
GLUE
Pretrain
BERT_BASE-sized encoder-decoder Transformer
Denoising objective
C4 dataset
2^19 steps
2^35 or ~34B tokens
Inverse square root learning rate schedule
2^18 steps
2^34 or ~17B tokens
Constant learning rate



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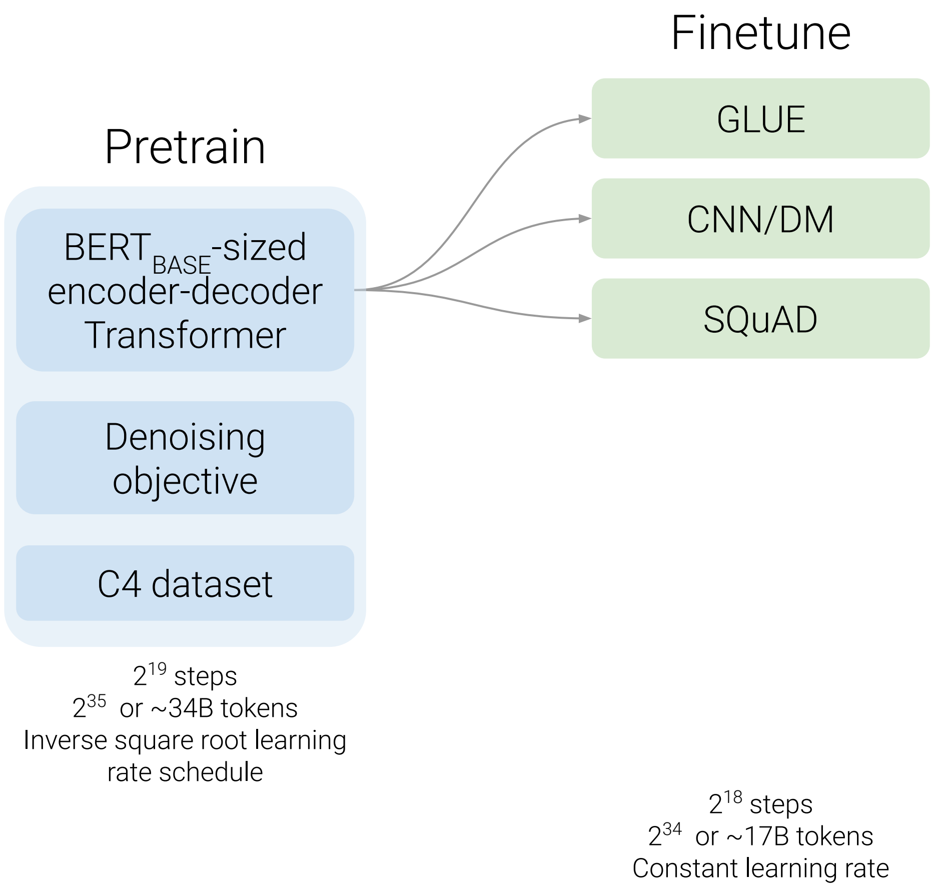
Pretrain
BERT_BASE-sized encoder-decoder Transformer
Denoising objective
C4 dataset
Finetune
GLUE
CNN/DM
SQuAD
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2^35 or ~34B tokens
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2^18 steps
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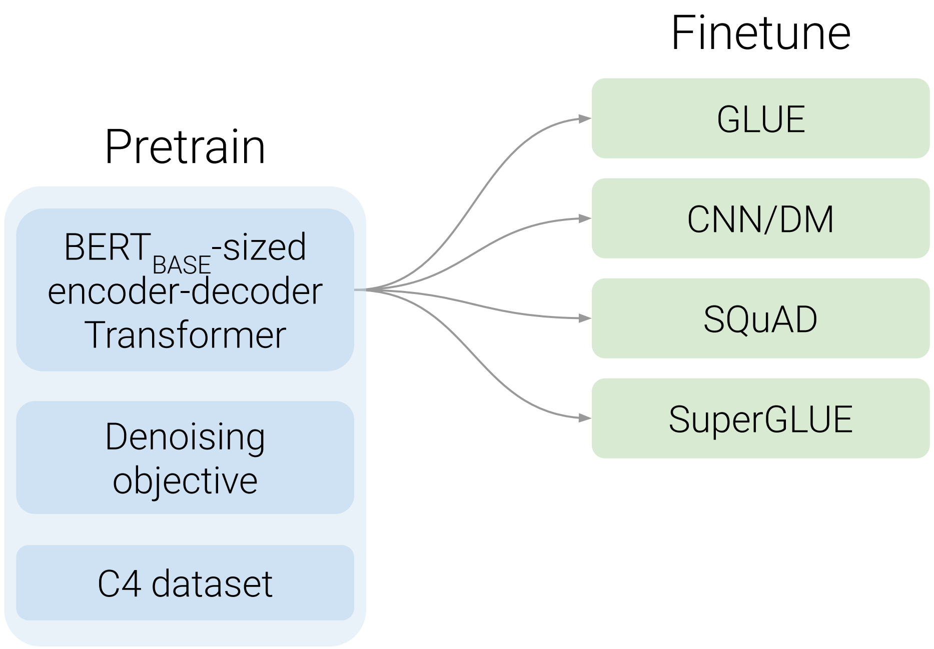

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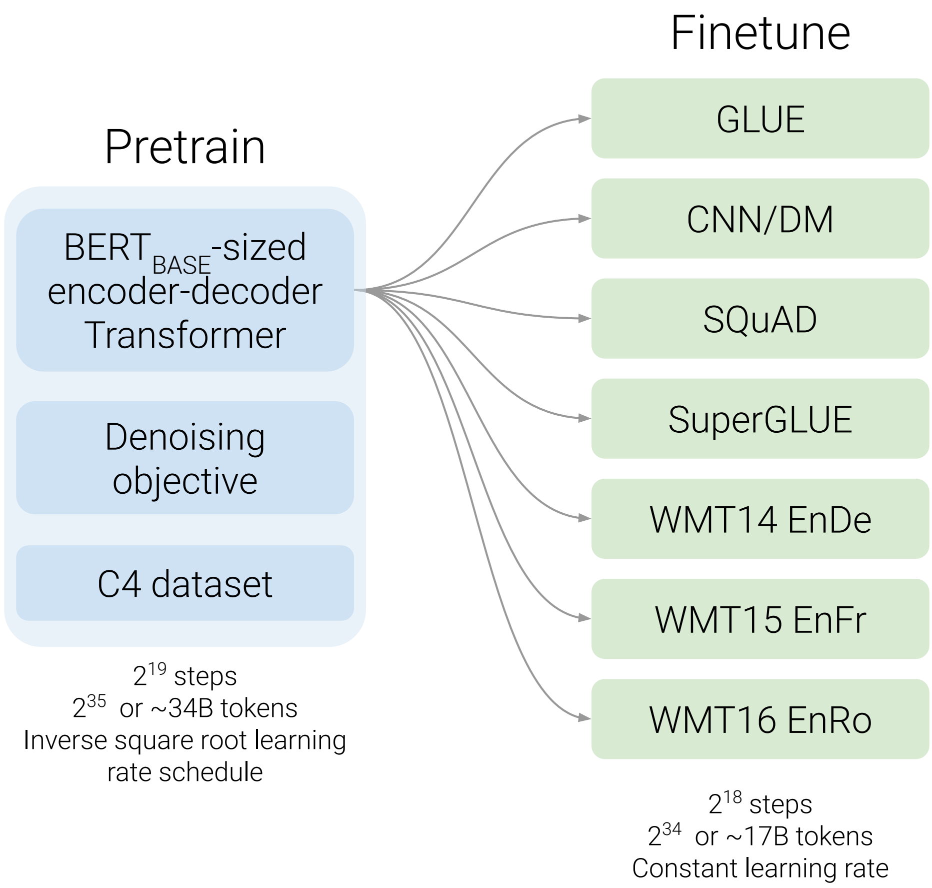
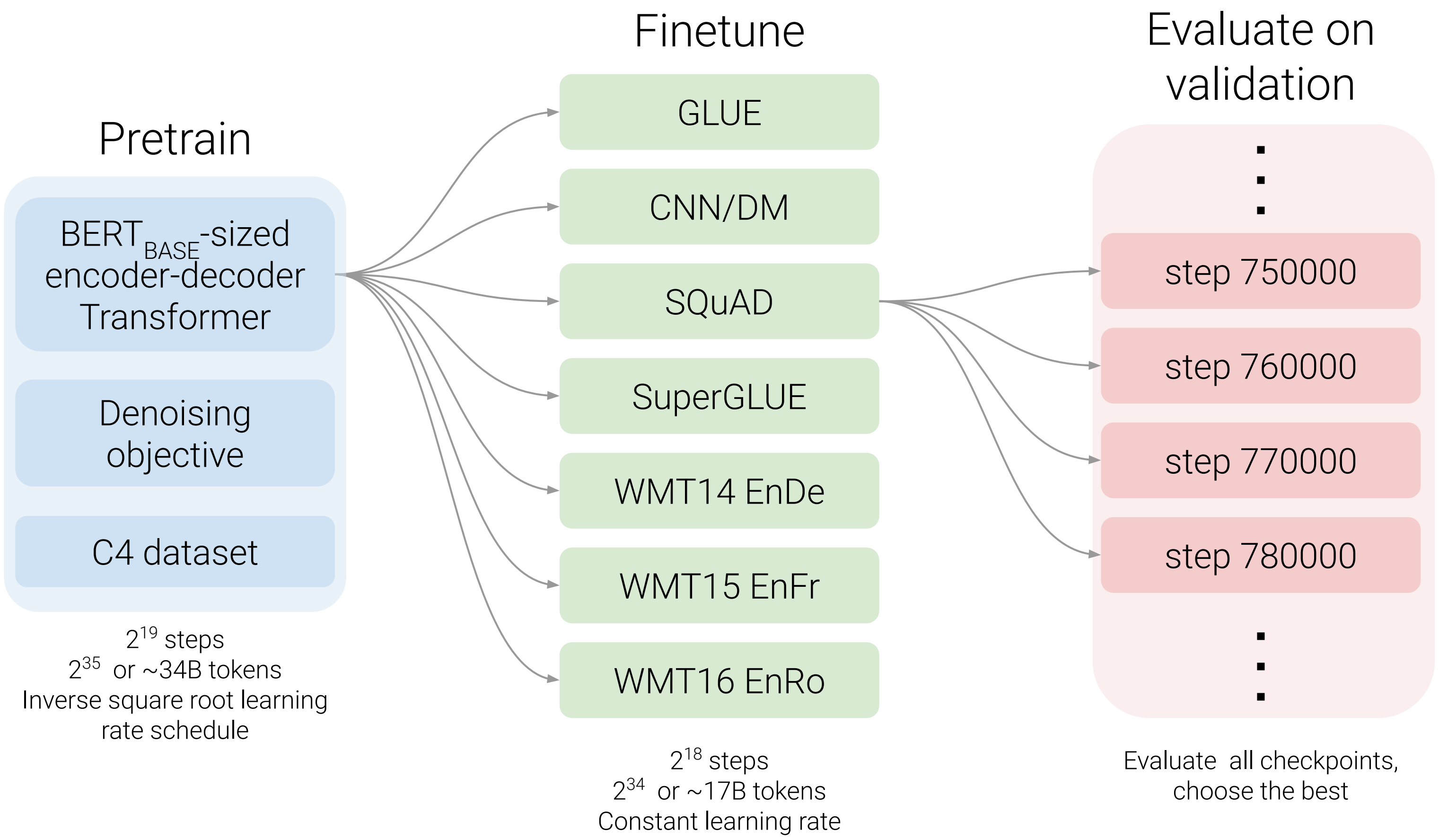


Pretrain
BERT$_{BASE}$-sized encoder-decoder Transformer
Denoising objective
C4 dataset
2^{19} steps
2^{35} or ~34B tokens
Inverse square root learning rate schedule
Finetune
GLUE
CNN/DM
SQuAD
SuperGLUE
WMT14 EnDe
WMT15 EnFr
WMT16 EnRo
2^{18} steps
2^{34} or ~17B tokens
Constant learning rate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SQuAD
SuperGLUE
WMT14 EnDe
WMT15 EnFr
WMT16 EnRo
2^{18} steps
2^{34} or ~17B tokens
Constant learning rate
Evaluate on validation
step 750000
step 760000
step 770000
step 780000
Evaluate all checkpoints, choose the best

	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
Setting 1							
Setting 2				*Downstream task 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

Bold = 1 std. dev. of max

Star denotes baseline

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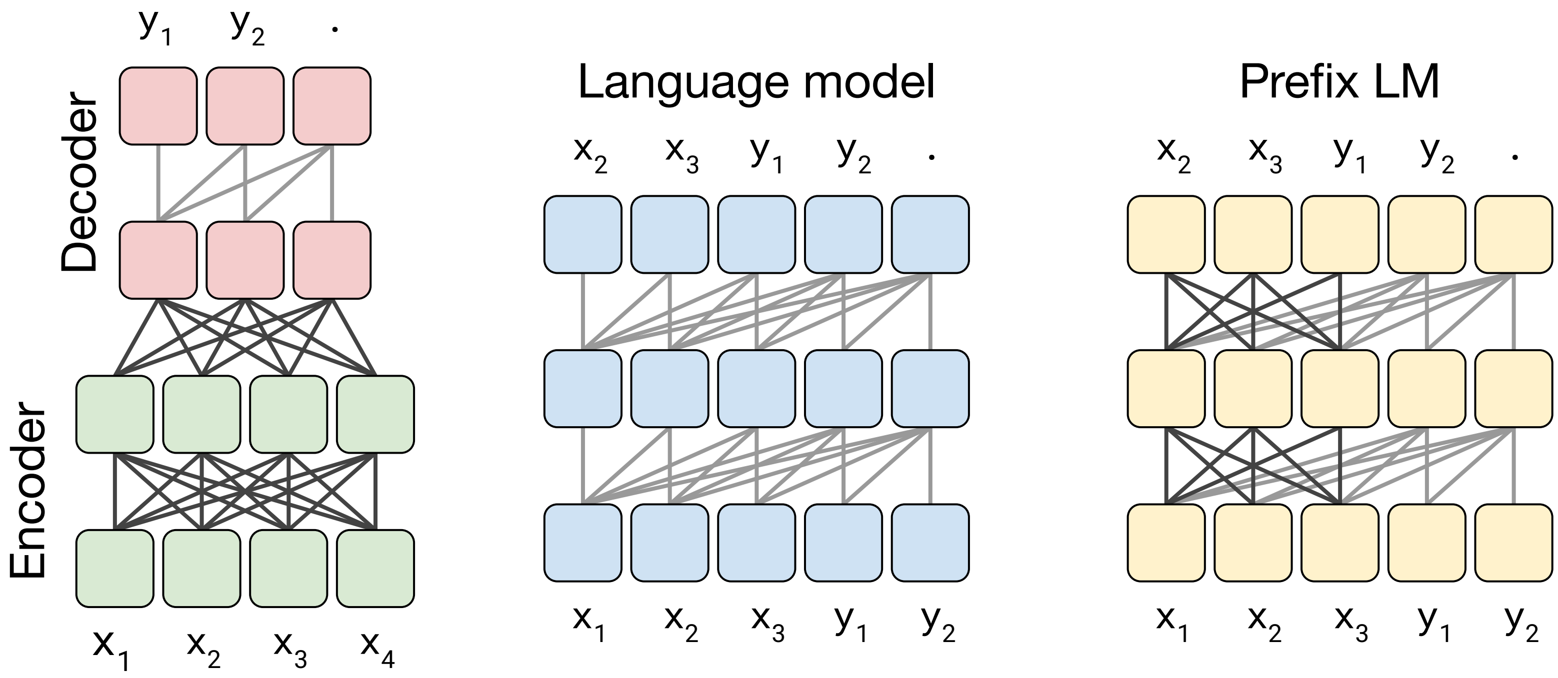
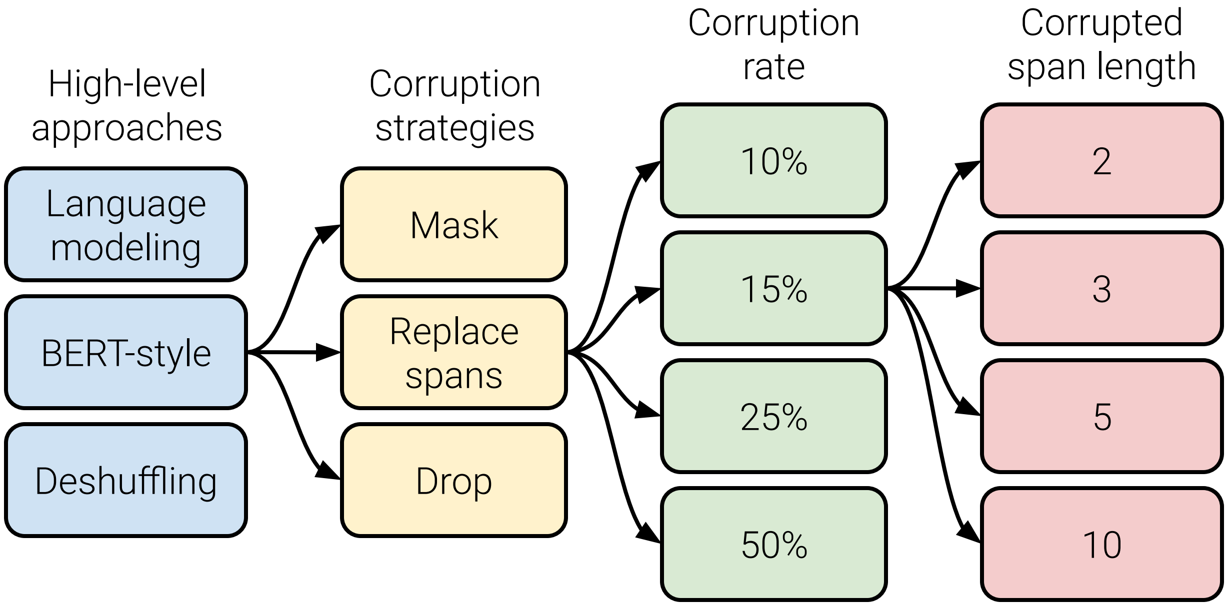
Big training set

Architecture	Params	Cost	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Encoder-decoder	$2P$	M	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
Enc-dec, shared	P	M	82.81	18.78	**80.63**	**70.73**	26.72	39.03	**27.46**
Enc-dec, 6 layers	P	$M/2$	80.88	18.97	77.59	68.42	26.38	38.40	26.95
Language model	P	M	74.70	17.93	61.14	55.02	25.09	35.28	25.86
Prefix LM	P	M	81.82	18.61	78.94	68.11	26.43	37.98	27.39





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**

	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**

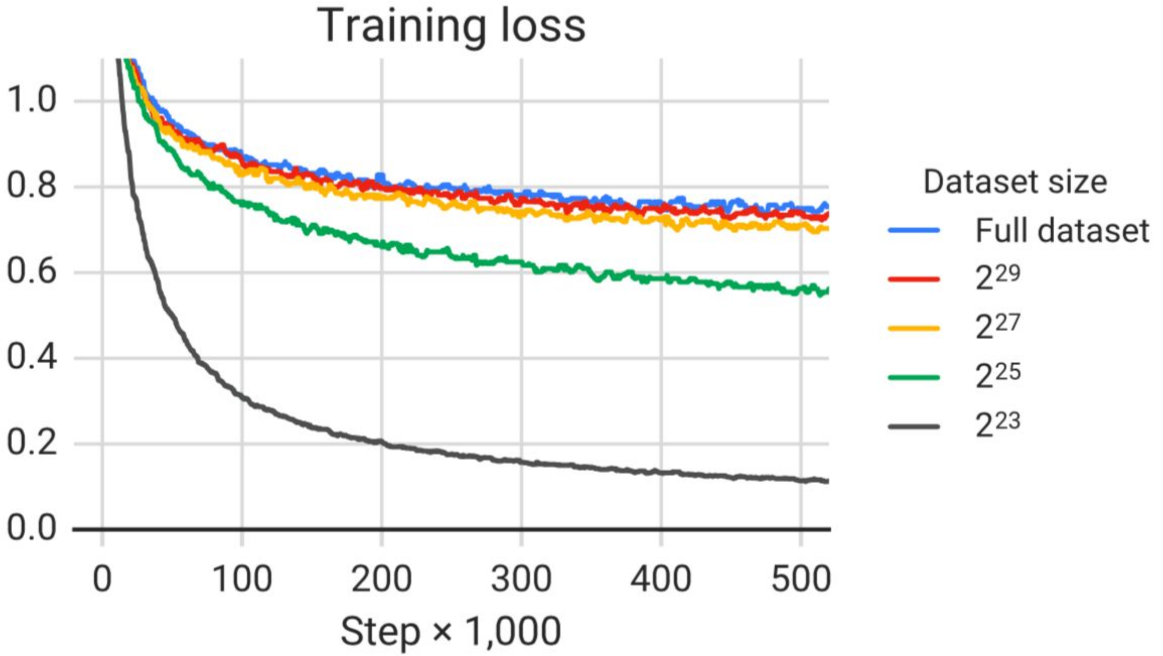
Much worse on CoLA

Much better on ReCoRD

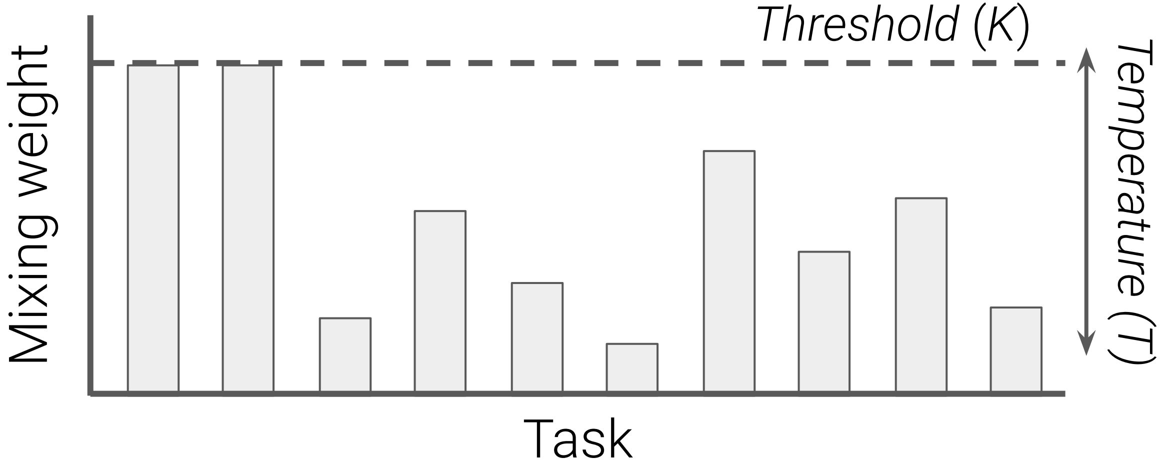
Order of magnitude smaller

Much better on MultiRC

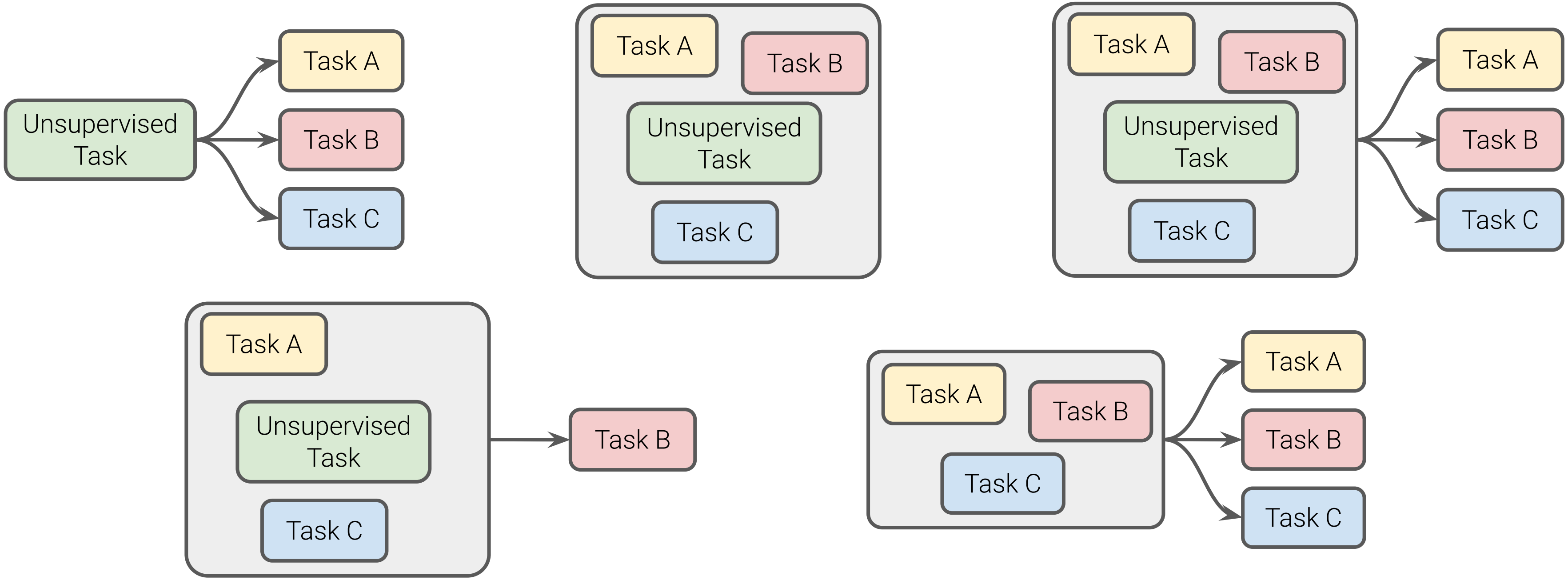
Number of tokens	Repeats	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Full dataset	0	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
2^{29}	64	**82.87**	**19.19**	**80.97**	**72.03**	**26.83**	**39.74**	**27.63**
2^{27}	256	82.62	**19.20**	79.78	69.97	**27.02**	**39.71**	27.33
2^{25}	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



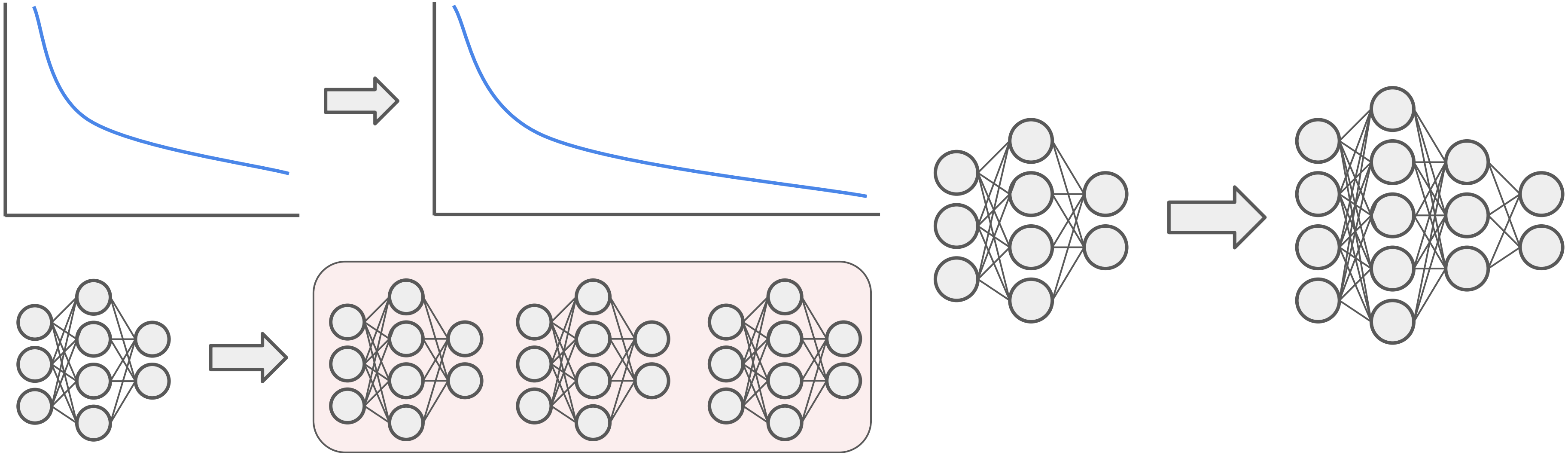
Mixing strategy	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Baseline (pre-train/fine-tine)	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
Equal	76.13	19.02	76.51	63.37	23.89	34.31	26.78
Examples-proportional, $K = 2^{16}$	80.45	19.04	77.25	69.95	24.35	34.99	27.10
Examples-proportional, $K = 2^{17}$	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



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**



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



Encoder-decoder architecture

	Architecture	Params	Cost	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★	Encoder-decoder	$2P$	M	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
	Enc-dec, shared	P	M	82.81	18.78	**80.63**	**70.73**	26.72	39.03	**27.46**
	Enc-dec, 6 layers	P	$M/2$	80.88	18.97	77.59	68.42	26.38	38.40	26.95
	Language model	P	M	74.70	17.93	61.14	55.02	25.09	35.28	25.86
	Prefix LM	P	M	81.82	18.61	78.94	68.11	26.43	37.98	27.39

Span prediction objective

	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**

C4 dataset

	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**

Multi-task pre-training

	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**

Bigger models trained longer

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

Model size variants

Model	Parameters	# layers	d_{model}	d_{ff}	d_{kv}	# heads
Small	60M	6	512	2048	64	8
Base	220M	12	768	3072	64	12
Large	770M	24	1024	4096	64	16
3B	3B	24	1024	16384	128	32
11B	11B	24	1024	65536	128	128

Back-translation beats English-only pre-training

Model	GLUE Average	CNN/DM ROUGE-2-F	SQuAD EM	SuperGLUE Average	WMT EnDe BLEU	WMT EnFr BLEU	WMT EnRo BLEU
Previous best	89.4	20.30	90.1	84.6	**33.8**	**43.8**	**38.5**
T5-Small	77.4	19.56	87.24	63.3	26.7	36.0	26.8
T5-Base	82.7	20.34	92.08	76.2	30.9	41.2	28.0
T5-Large	86.4	20.68	93.79	82.3	32.0	41.5	28.1
T5-3B	88.5	21.02	94.95	86.4	31.8	42.6	28.2
T5-11B	**90.3**	**21.55**	**91.26**	**89.3**	32.1	43.4	28.1

Human score = 89.8

google-research / text-to-text-transfer-transformer

<> Code | Issues 8 | Pull requests 1 | Actions | Projects 0 | Wiki | Security | Insights | Settings

Code for the paper "Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer" https://arxiv.org/abs/1910.10683

Edit

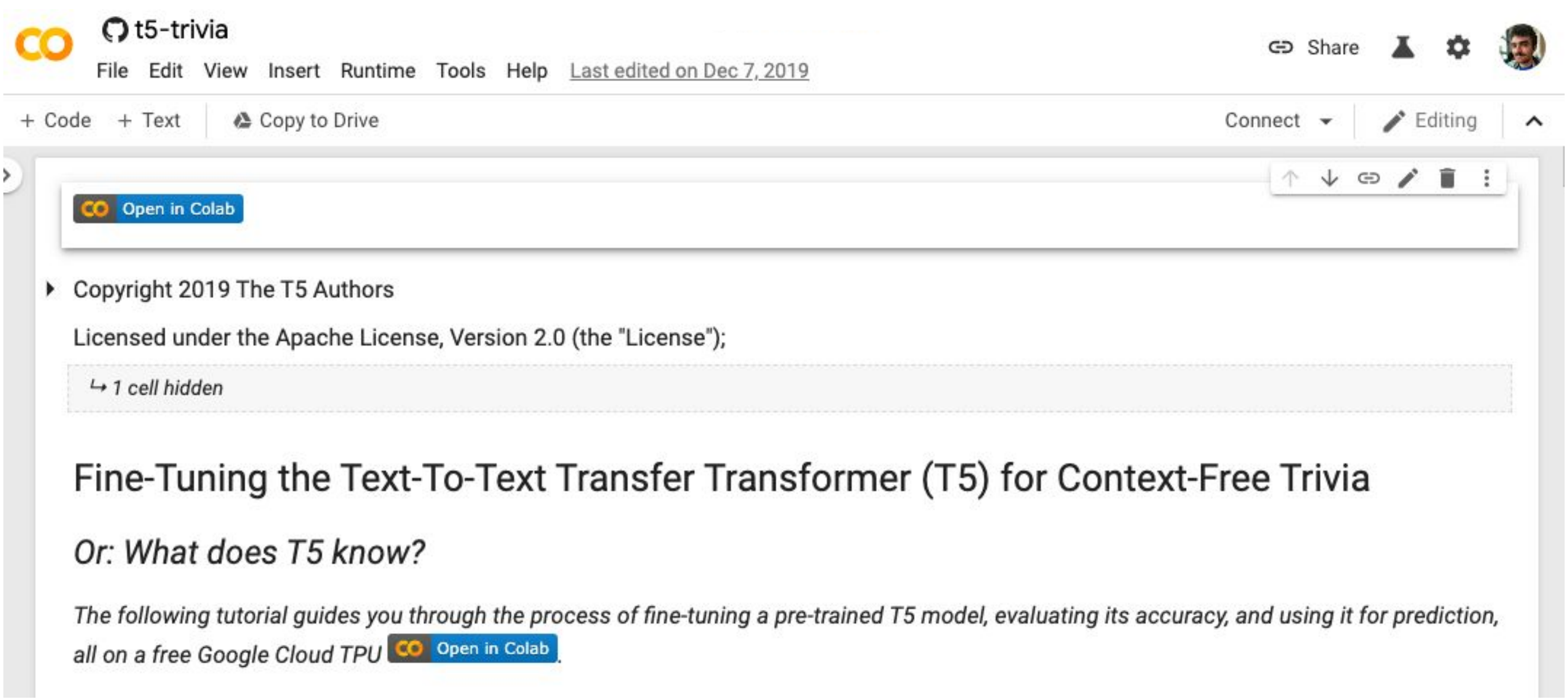
Manage topics

Released Model Checkpoints

We have released the following checkpoints for pre-trained models described in our paper:

- **T5-Small** (60 million parameters): gs://t5-data/pretrained_models/small
- **T5-Base** (220 million parameters): gs://t5-data/pretrained_models/base
- **T5-Large** (770 million parameters): gs://t5-data/pretrained_models/large
- **T5-3B** (3 billion parameters): gs://t5-data/pretrained_models/3B
- **T5-11B** (11 billion parameters): gs://t5-data/pretrained_models/11B

https://github.com/google-research/text-to-text-transfer-transformer



http://tiny.cc/t5-colab

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french, italian, thai, vietnamese, chinese, ...

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the signing of the treaty formally ended the seven years' war, known as the french and indian war in the north american theatre,[1] and marked the beginning of an era of british dominance outside europe.[2] great britain and france each returned much of the territory that they had captured during the war, but great britain gained much of france's possessions in north america. additionally, great britain agreed to protect roman catholicism in the new world...

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is designed to distribute the
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operator, so enabling the convenient carriage of
heavier and bulkier loads than would be possible
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as such it is a second-class lever...

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== treaty o

== piano

the piano is an acoustic, stringed musical instrument invented in italy by bartolomeo cristofori around the year 1700 (the exact year is uncertain), in which the strings are struck by hammers. it is played using a keyboard,[1] which is a row of keys (small levers) that the performer presses down or strikes with the fingers and thumbs of both hands to cause the hammers to strike the strings.

the word piano is a shortened form of pianoforte, the italian term for the early 1700s versions of the instrument, which in turn derives from gravicembalo col piano e forte[2] and fortepiano. the italian musical terms piano and forte indicate

greed to protect roman
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paris, also known as the treaty
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f the treaty formally ended the
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erican theatre,[1] and marked t
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territory that they had captured
ar, but great britain gained muc
sessions in north america.

== lemon

the lemon, citrus limon (l.) osbeck, is a species of
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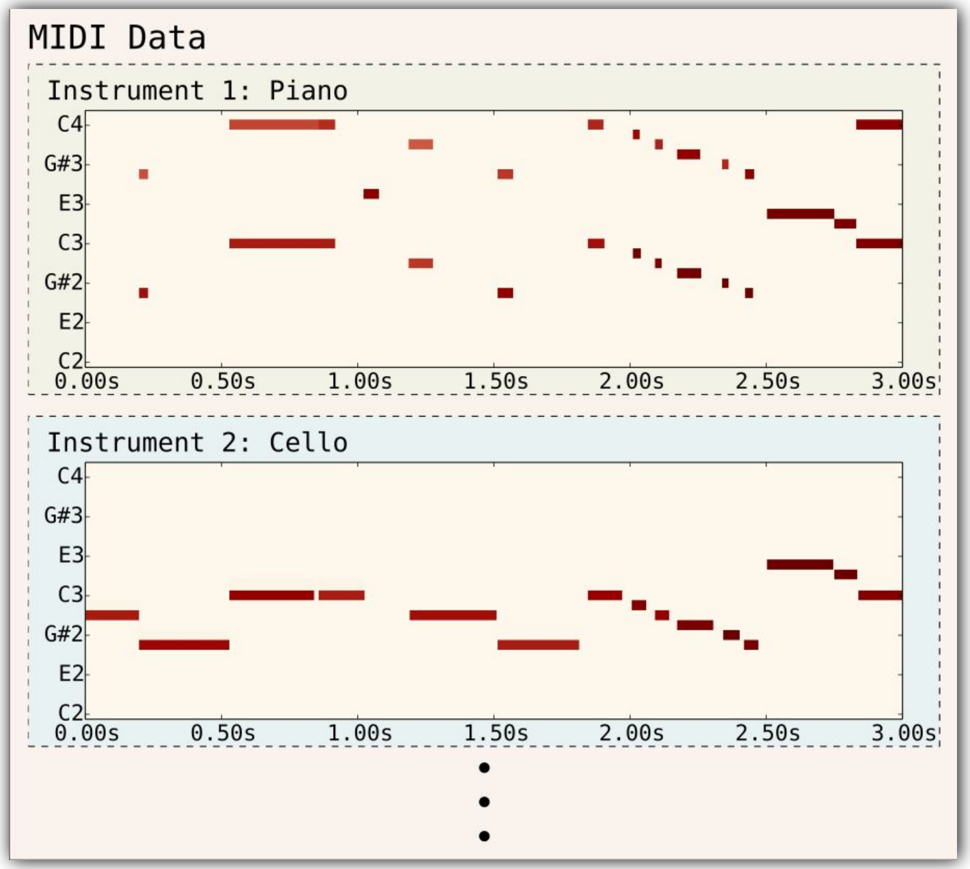
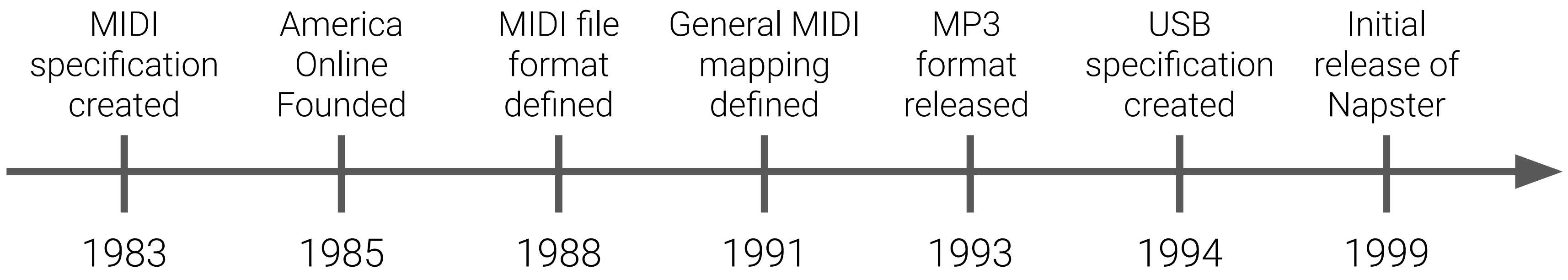
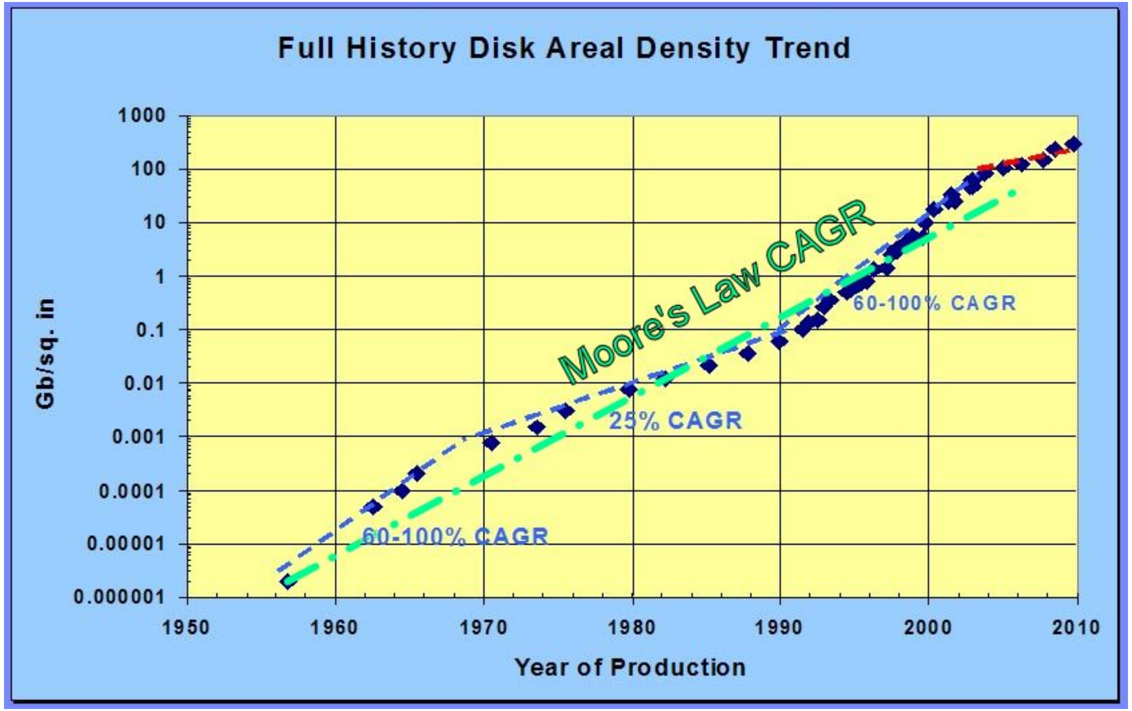
== wheelbarrow

a wheelbarrow is a small hand-propelled vehicle, usually with just one wheel, designed to be pushed and guided by a single person using two handles at the rear, or by a sail to push the ancient wheelbarrow by wind. the term "wheelbarrow" is made of two words: "wheel" and "barrow." "barrow" is a derivation of the old english "bearwe" which was a device used for carrying loads.


MIDI FILES
HISTORY.COM
imgflip.com


MIDI Data
Instrument 1: Piano
C4
G#3
E3
C3
G#2
E2
C2
0.00s
0.50s
1.00s
1.50s
2.00s
2.50s
3.00s
Instrument 2: Cello
C4
G#3
E3
C3
G#2
E2
C2
0.00s
0.50s
1.00s
1.50s
2.00s
2.50s
3.00s


MIDI specification created
1983
America Online Founded
1985
MIDI file format defined
1988
General MIDI mapping defined
1991
MP3 format released
1993
USB specification created
1994
Initial release of Napster
1999

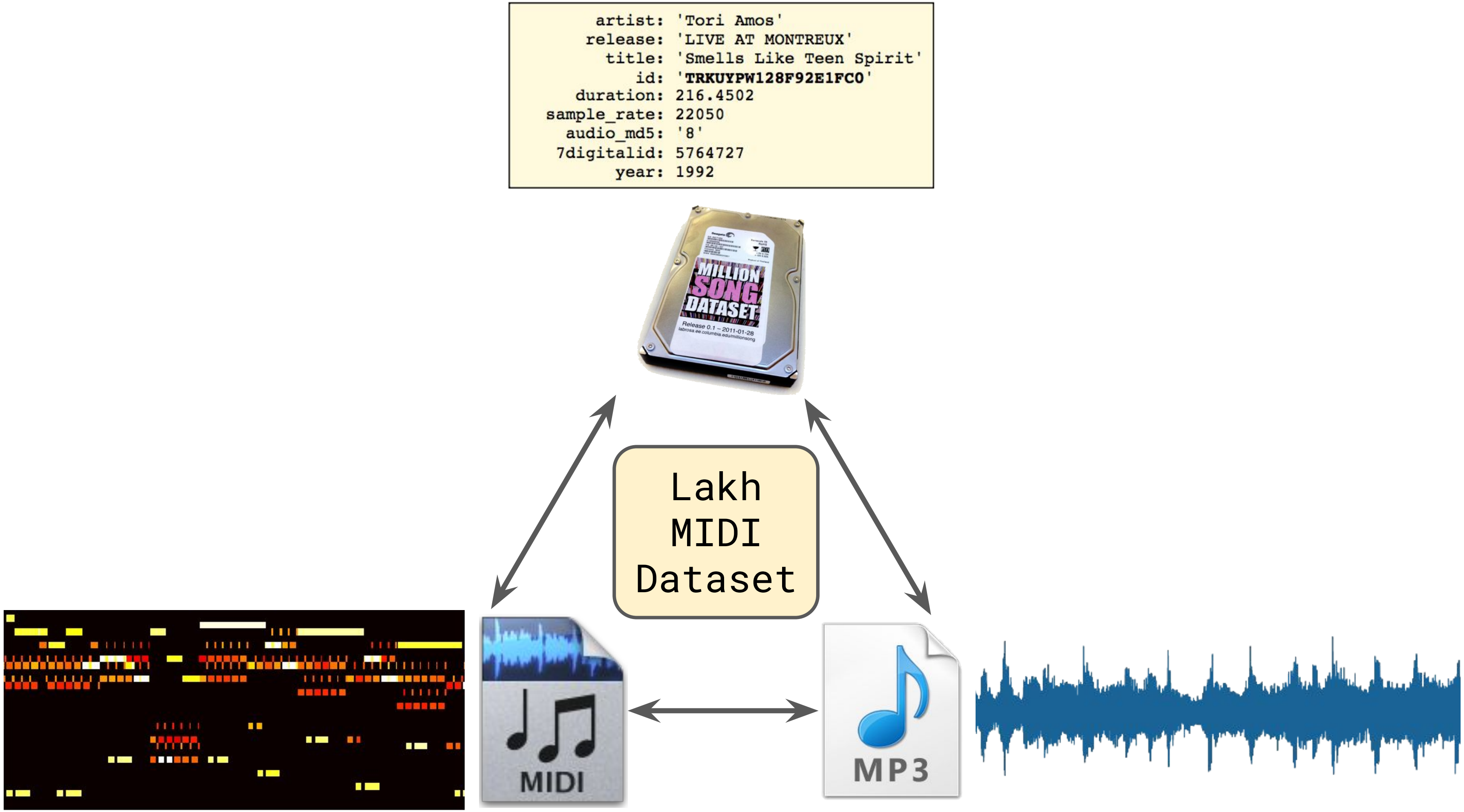


“Prediction: The cost for 128 kilobytes of memory will fall below U$100 in the near future.“

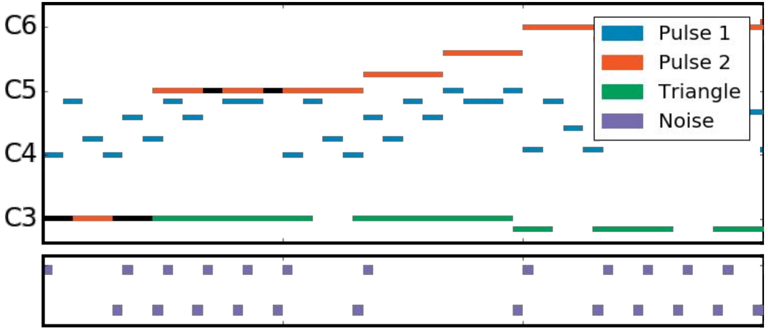
Creative Computing magazine
December 1981, page 6

Photo by user Barry Whyte, Wikipedia, CC-BY-SA


DIGITAL



http://colinraffel.com/projects/lmd/ http://bit.ly/lmd-tutorial



NO_NOTEON_13, DT_732, NO_NOTEOFF, DT_2197,
P1_NOTEON_76, DT_2, P1_NOTEON_70, DT_1463,
P2_NOTEON_87, DT_1, P2_NOTEOFF, DT_148,
…
P1_NOTEON_61, DT_41, P2_NOTEON_85, DT_26,
TR_NOTEON_39, DT_2, TR_NOTEON_43, DT_23,
NO_NOTEON_9, DT_646, NO_NOTEON_13, DT_733

NES MIDI → Events → *Transformer-XL* [Dai+ 2019]

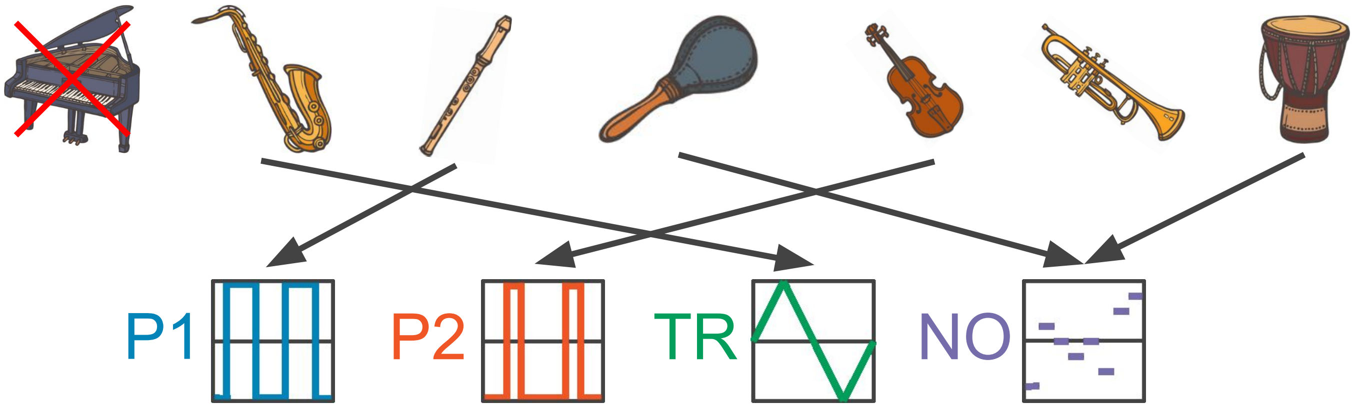
Slide from Chris Donahue

NES-MDB
(Donahue+ 2018)
46 hours

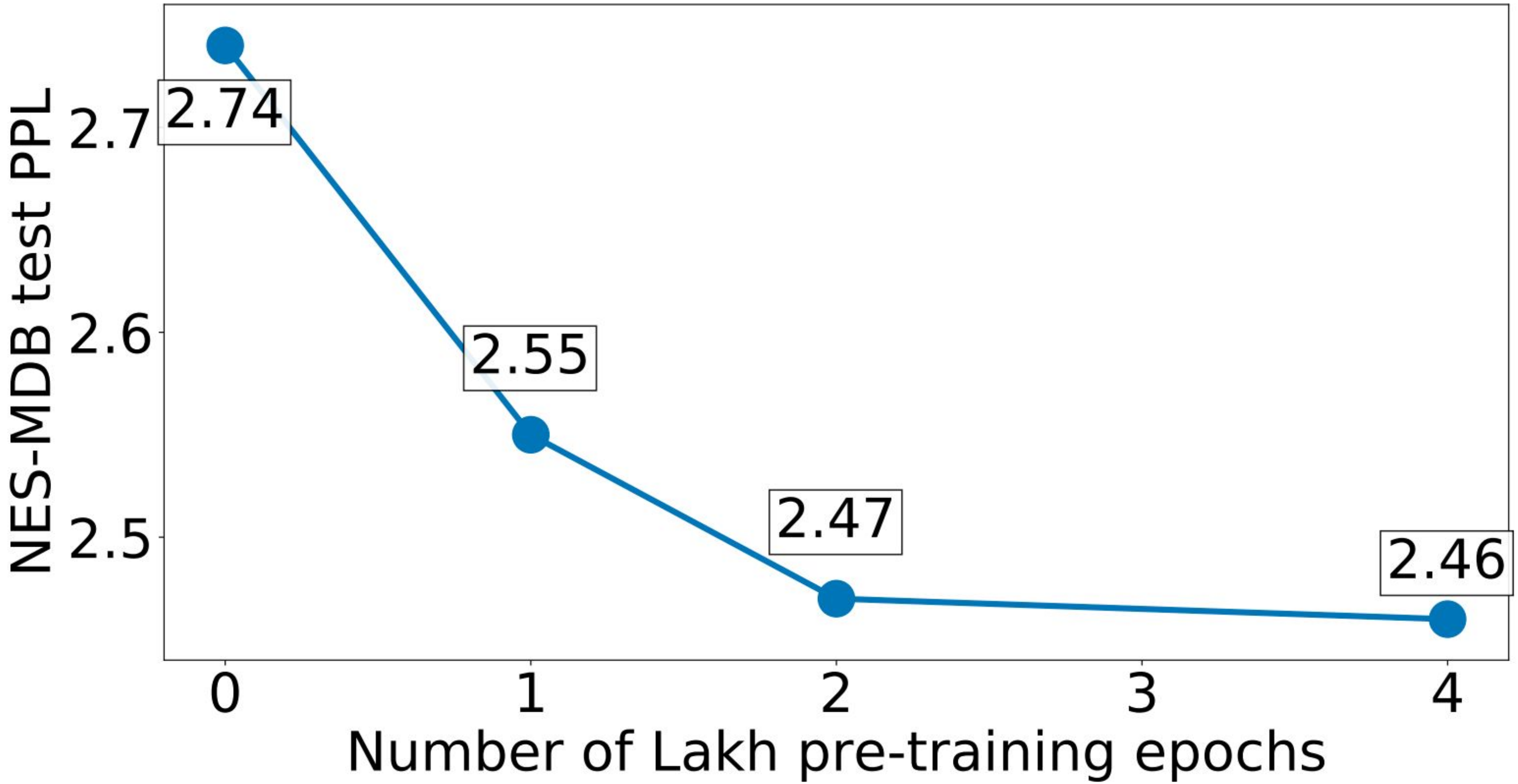
Lakh MIDI Dataset
9000+ hours

Slide from Chris Donahue

Goal: Pre-train on Lakh MIDI dataset, fine-tune on NES-MDB

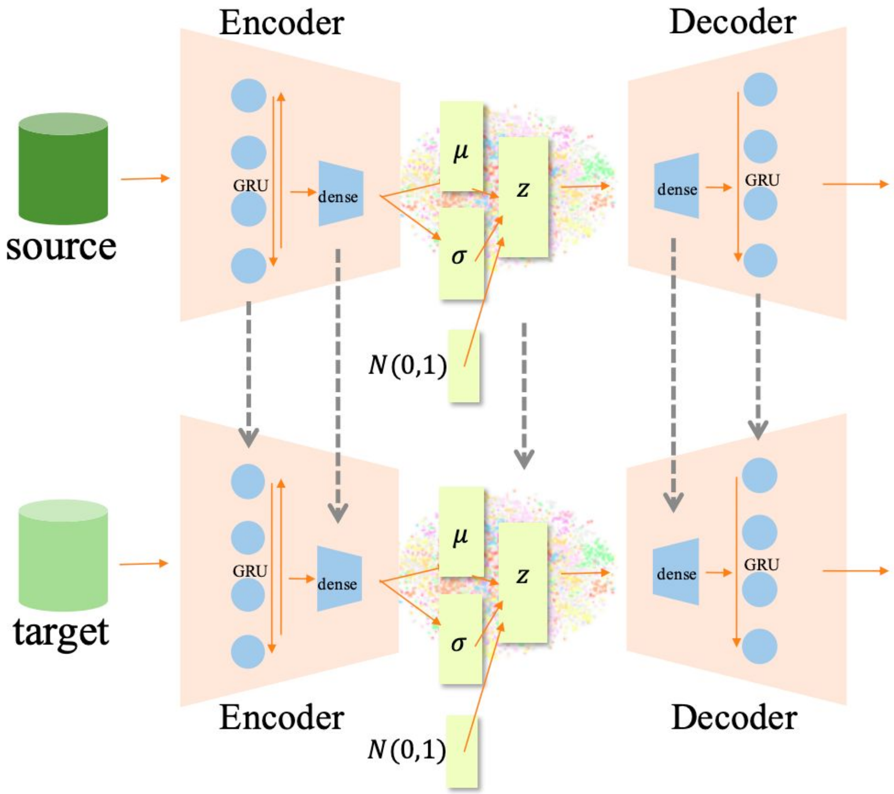


Slide from Chris Donahue

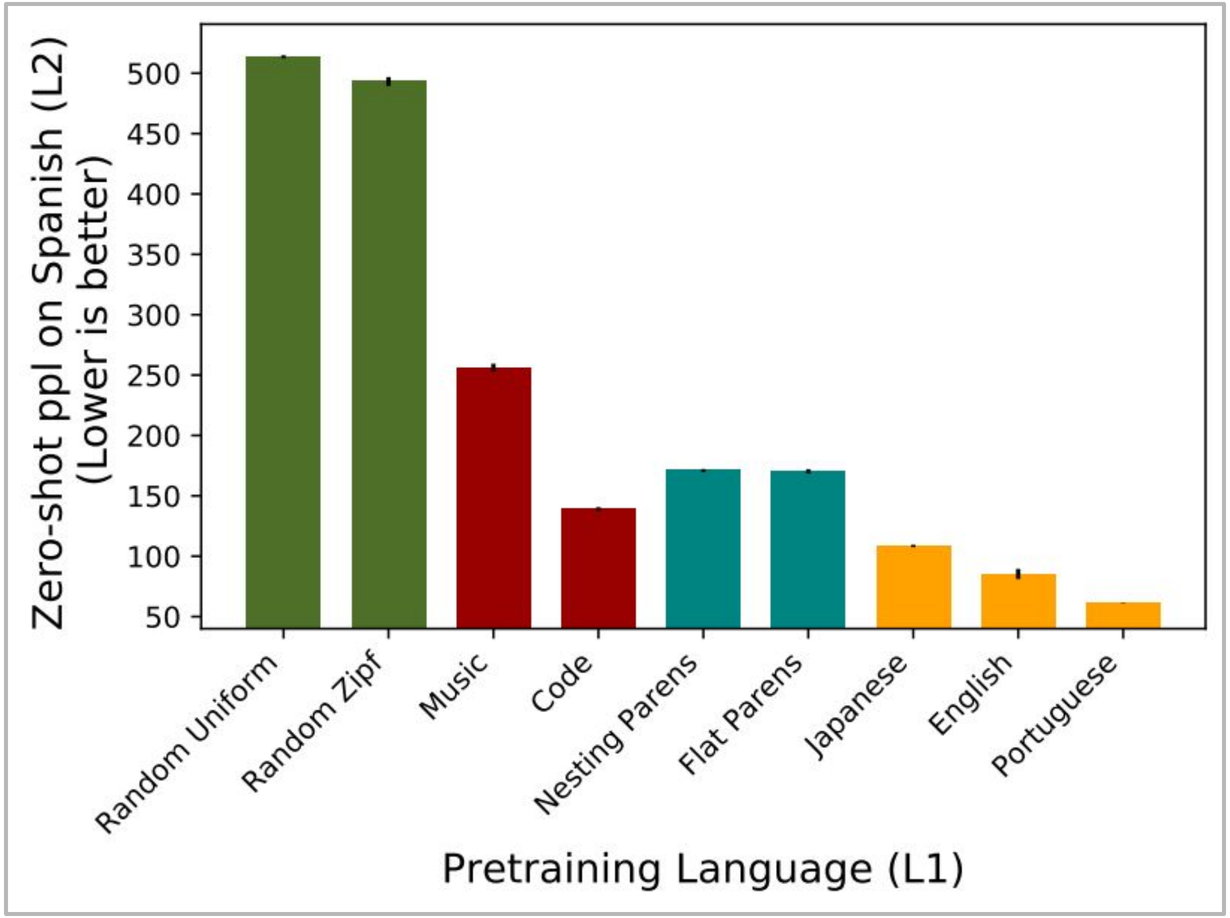


NES-MDB test PPL
2.7
2.6
2.5
2.74
2.55
2.47
2.46
0
1
2
3
4
Number of Lakh pre-training epochs

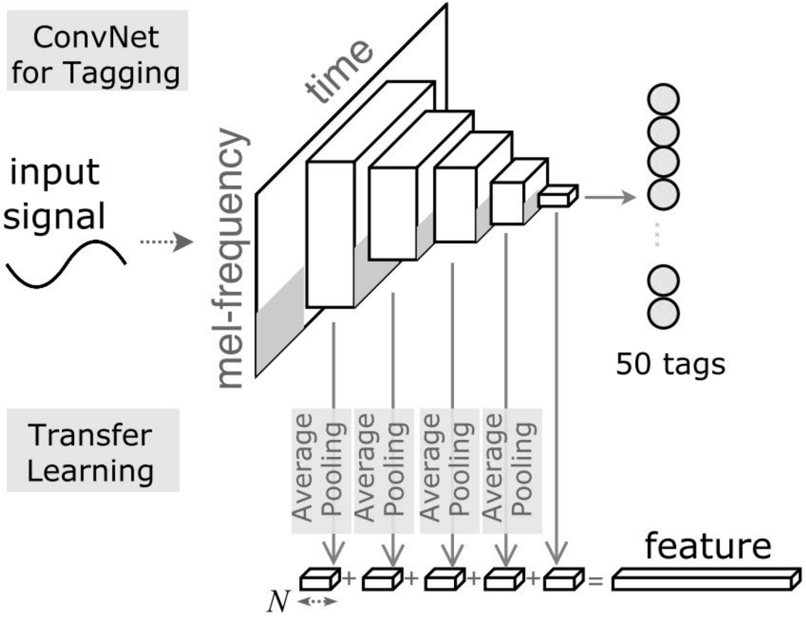
	TT (source)	CY+R (target)
Genre	diverse	Jazz only
Song length	segment	segment
Track	melody, chord	melody
Musical key	C major, C minor	C major
Time signature	4/4	4/4
Number of phrases	9,640	1,608
Number of bars	38,560	6,432



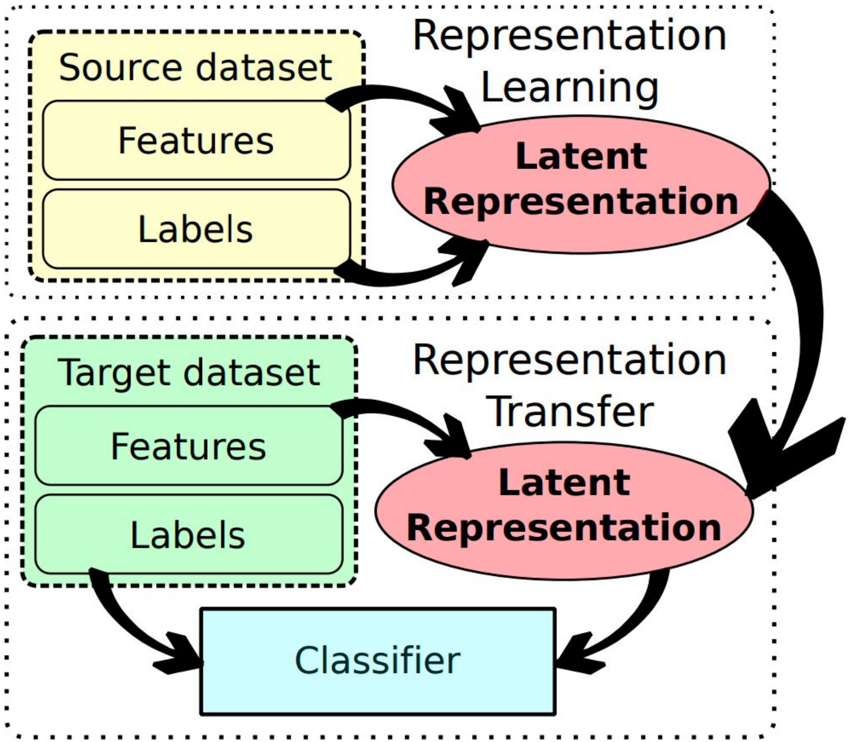
"Improving Automatic Jazz Melody Generation by Transfer Learning Techniques", Hung et al. 2019



"Learning Music Helps You Read: Using Transfer to Study Linguistic Structure in Language Models", Papadimitriou & Jurafsky, 2020



"Transfer Learning for Music Classification and Regression Tasks", Choi et al. 2017



"Transfer Learning in MIR: Sharing Learned Latent Representations for Music Audio Classification and Similarity", Hamel et al. 2013

“Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer”, Raffel, Shazeer, Roberts, Lee et al. 2019

“Learning-Based Methods for Comparing Sequences, with Applications to Audio-to-MIDI Alignment and Matching”, Raffel 2016

“LakhNES: Improving multi-instrumental music generation with cross-domain pre-training”, Donahue et al. 2019

“Improving Automatic Jazz Melody Generation by Transfer Learning Techniques”, Hung et al. 2019

“Learning Music Helps You Read: Using Transfer to Study Linguistic Structure in Language Models”, Papadimitriou & Jurafsky, 2020

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Thanks! Questions?