# Data Efficiency

## NLP: Fall 2024

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# Shortformer: Better Language Modeling Using Shorter Inputs

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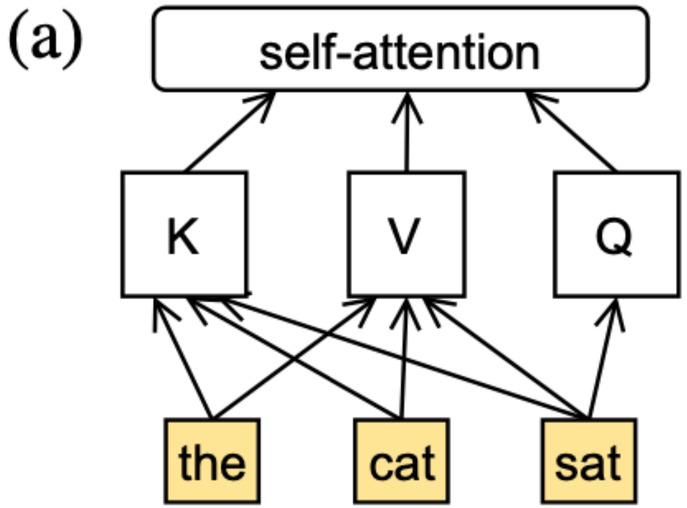
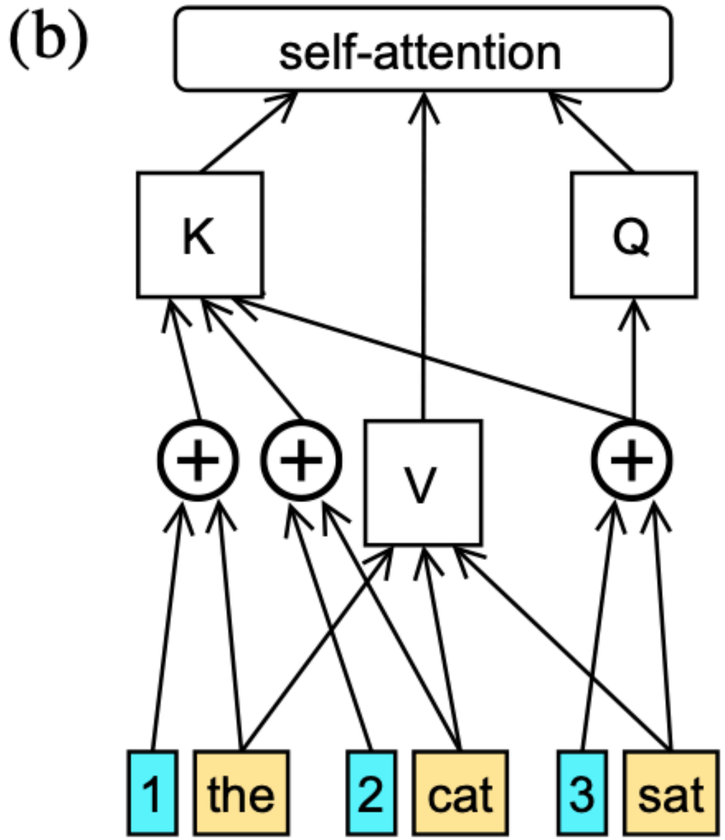
https://aclanthology.org/2021.acl-long.427/

# ShortFormer

- **Staged Training** aka Curriculum Learning
  - Training on shorter subsequences (before moving on to longer ones) leads to faster and more memory-efficient training. Also improves perplexity.
- **Position infused Attention**
    - Transformer XL used cached previously evaluated sequences using *relative* position embeddings to scale to longer inputs
    - Instead of adding absolute position embeddings to the tokens, add positional embeddings directly into the attention layer (keys and queries)
    - Get rid of position embeddings at the token level

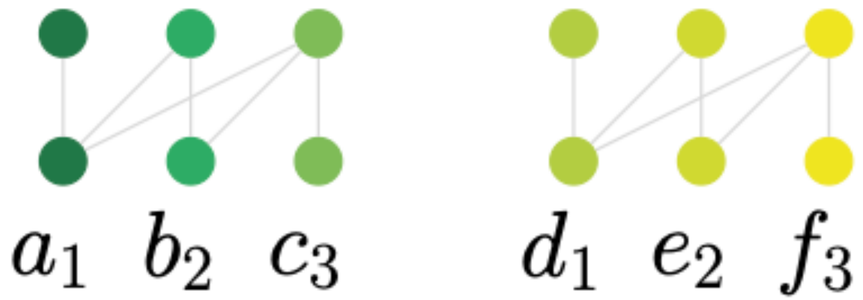



Standard Attention

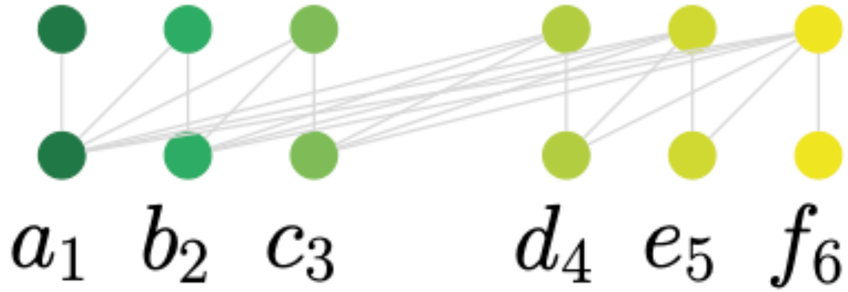



Position Infused Attention
(enables caching)

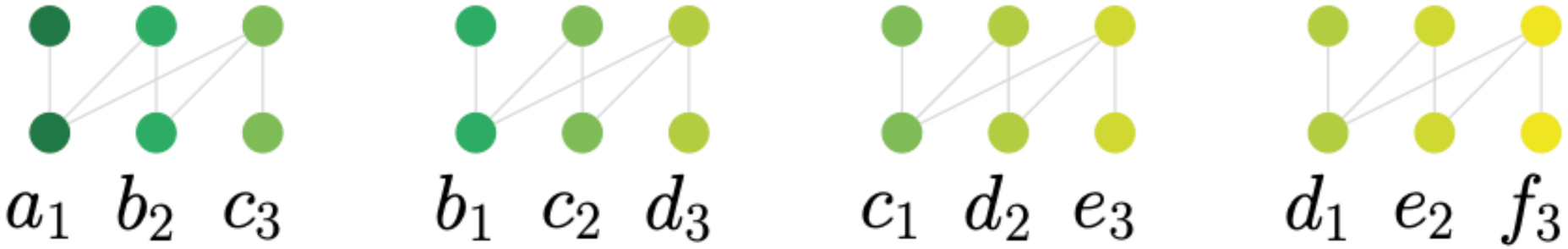
# Train on short; inference on long




Non-overlapping




Caching (using PIA)




Sliding window with stride S=1

| Subseq. Length | Train | Inference | | | |
|---|---|---|---|---|---|
| | | Nonoverlapping | | Sliding Window (Token-by-token) | |
| | Speed ↑ | PPL ↓ | Speed ↑ | PPL ↓ | Speed ↑ |
| 32 | 28.3k | 35.37 | 2.4k | 24.98 | **74** |
| 64 | 28.5k | 28.03 | 4.8k | 21.47 | 69 |
| 128 | **28.9k** | 23.81 | 9.2k | 19.76 | 70 |
| 256 | 28.1k | 21.45 | 14.8k | 18.86 | 63 |
| 512 | 26.1k | 20.10 | 18.1k | 18.41 | 37 |
| 1024 | 22.9k | 19.11 | **18.3k** | 17.97 | 18 |
| 1536 | 18.4k | 19.05 | 17.1k | 18.14 | 11 |
| 3072 | 13.9k | **18.65** | 14.7k | **17.92** | 5 |

| First Stage Subseq. Length | Train Speed ↑ | Inference PPL ↓ |
|---|---|---|
| 32 | 21.6k | 17.66 |
| 64 | 22.6k | 17.56 |
| 128 | **22.9k** | **17.47** |
| 256 | 22.5k | 17.50 |
| PIA + Cache w/o Staged Training | 21.5k | 17.85 |

| Model | Param. ↓ | Train | Inference (Test) | | |
|---|---|---|---|---|---|
| | | Speed ↑ | Mode | Speed ↑ | PPL ↓ |
| Baseline | **247M** | 13.9k | N.o. | **14.7k** | 19.40 |
| | | | S.W. | 2.5k | 18.70 |
| TransformerXL* | 257M | 6.0k | N.o. | 3.2k | 18.30 |
| Sandwich T. | **247M** | 13.9k | S.W. | 2.5k | 17.96 |
| Compressive T. | 329M | - | N.o. | - | 17.1 |
| Routing T. | - | - | N.o | - | 15.8 |
| kNN-LM** | **247M** | 13.9k | S.W. | 145 | **15.79** |
| PIA + Caching | **247M** | 21.5k | N.o. | 14.5k | 18.55 |
| Staged Training | **247M** | 17.6k | S.W. | 2.5k | 17.56 |
| Shortformer | **247M** | **22.9k** | N.o. | 14.5k | 18.15 |

# Do We Need to Create Big Datasets to Learn a Task?

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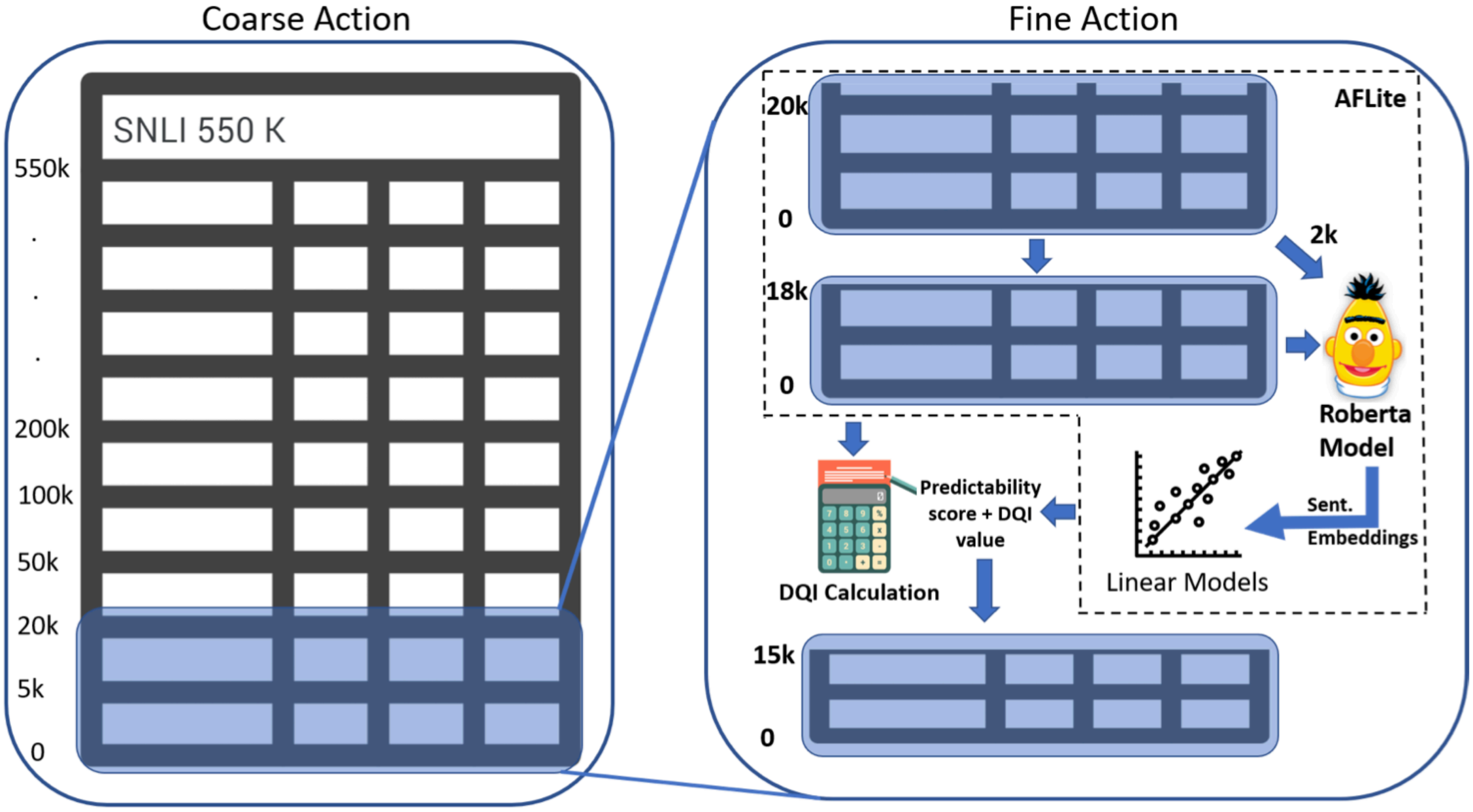
https://aclanthology.org/2020.sustainlp-1.23/

# Active Learning for Fine-tuning LLMs

- **Coarse action**
  - Start with random a% of the data and calculate accuracy on heldout data
  - Pick the best performing data and add b% and redo accuracy
  - Continue adding b% of training data until accuracy on heldout data does not increase
- **Fine action**
  - For each training set, randomly drop 10%, randomly divide into train/test, sort by the Data Quality Index (DQI) for bias detection
  - Short list the training data that scores greater than a threshold in DQI


Coarse Action
SNLI 550 K
550k
200k
100k
50k
20k
5k
0
Fine Action
20k
0
AFLite
2k
18k
0
Roberta Model
Predictability score + DQI value
DQI Calculation
Sent. Embeddings
Linear Models
15k
0

# Active Learning for Fine-tuning LLMs

- SNLI dataset
- a=5000; b=5000
- **Coarse action** finds 20K training examples
- **Fine action** can further reduce this to 5K-15K

Coarse

| Size | Performance on IID test set |
|---|---|
| 5000 | 36.77 |
| 10000 | 77.45 |
| 15000 | 81.69 |
| 20000 | **84.69** |
| 25000 | 80.96 |

Fine

| Size | IID Test |
|---|---|
| 550k | **89.64** |
| 20k | 84.69 |
| 5k | 87.47 |
| 8k | 87.54 |
| 10k | 87.93 |
| 12k | 88.56 |
| 15k | 88.95 |