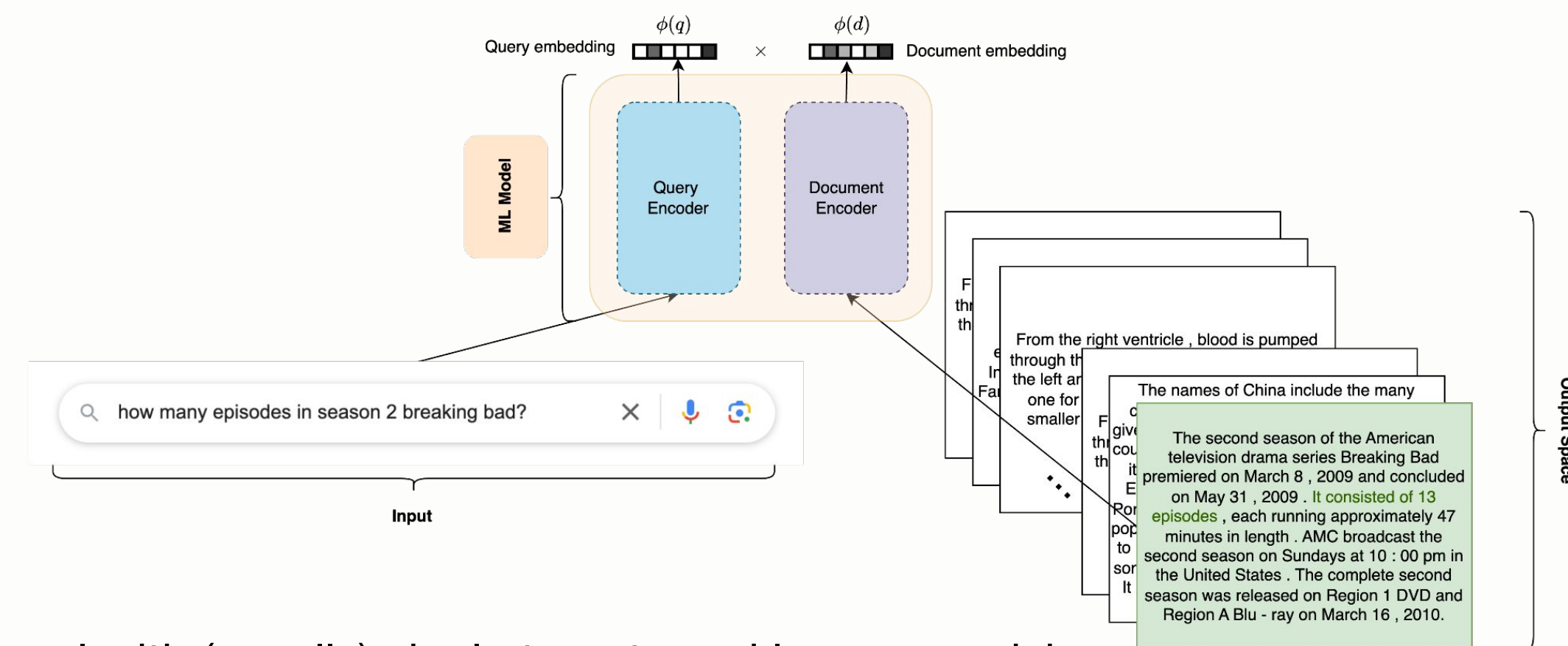




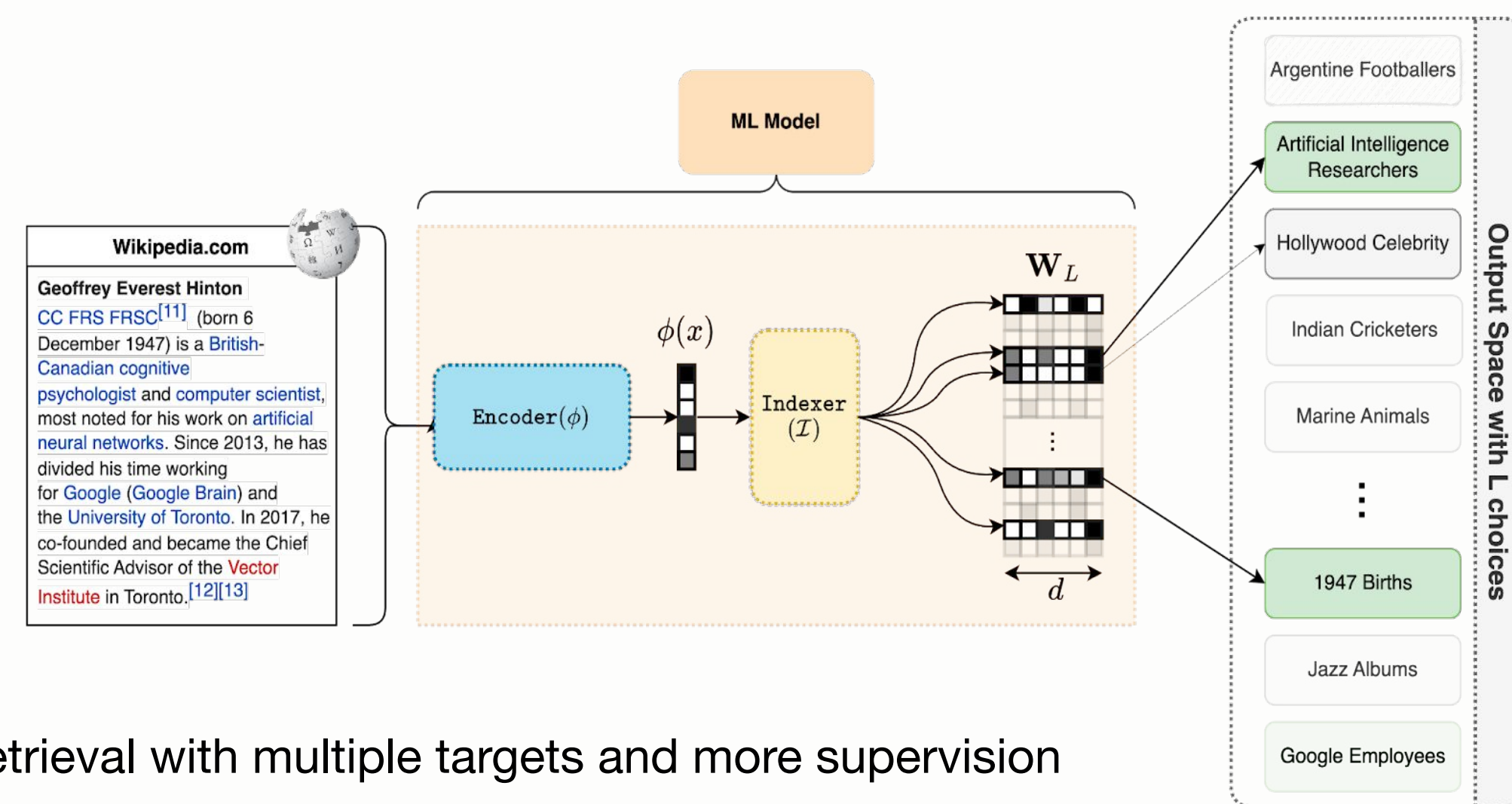
Dual-encoders for Extreme Multi-label Classification

Information Retrieval



Retrieval with (usually) single targets and less supervision

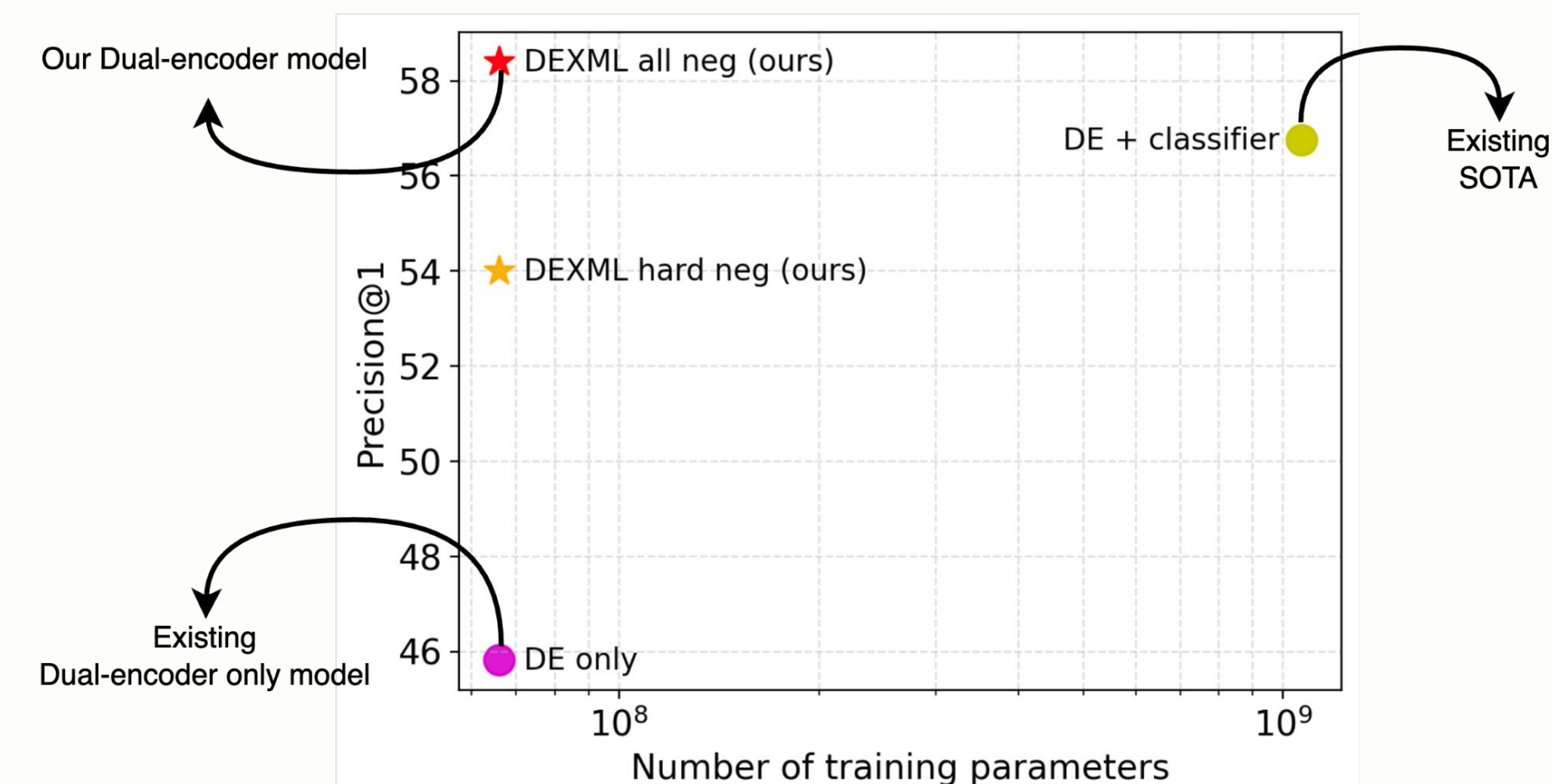
Extreme Multi-label Classification (XMC)



Retrieval with multiple targets and more supervision

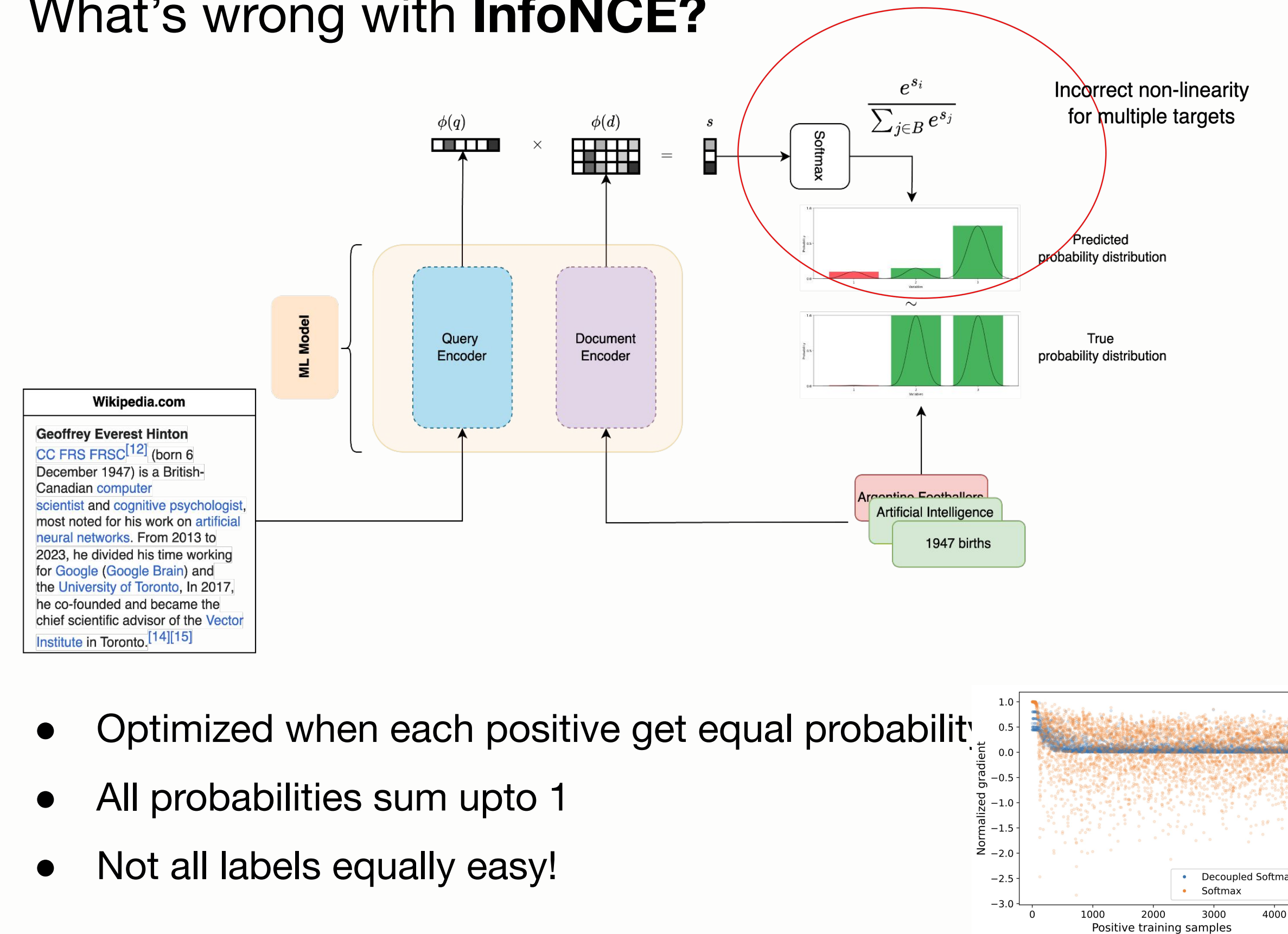
Dual-encoders (DE) for XMC?

- Model doesn't grow linearly with output space
- Better generalization on unseen items
- Struggle with semantic gap
- Underperform due to less capacity bad memorization



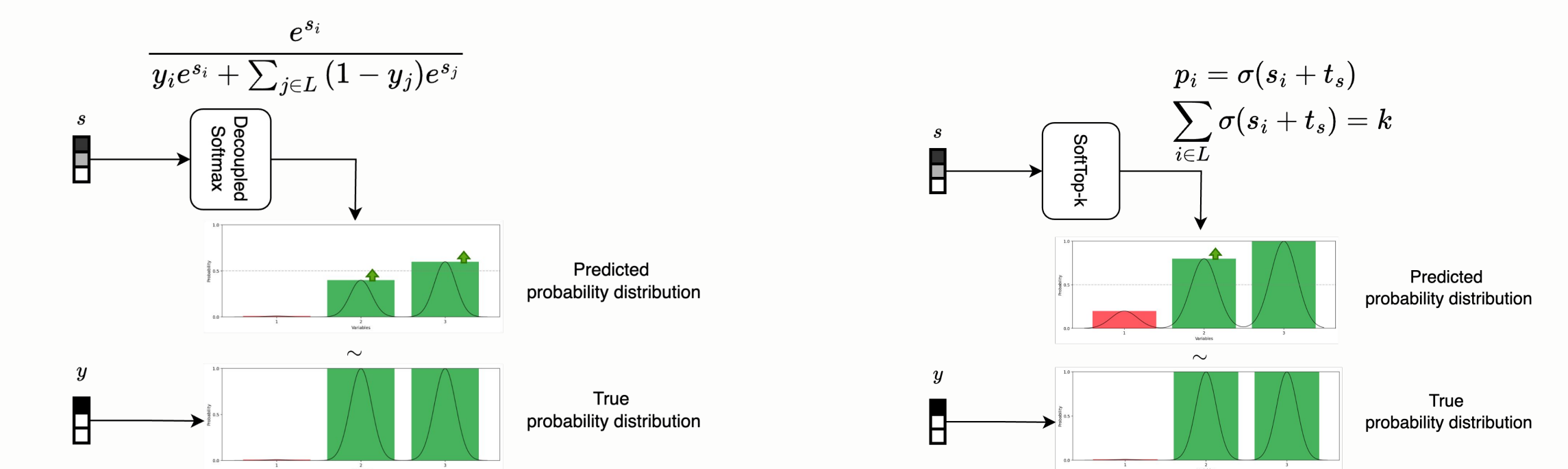
Research problem and Solution

What's wrong with InfoNCE?



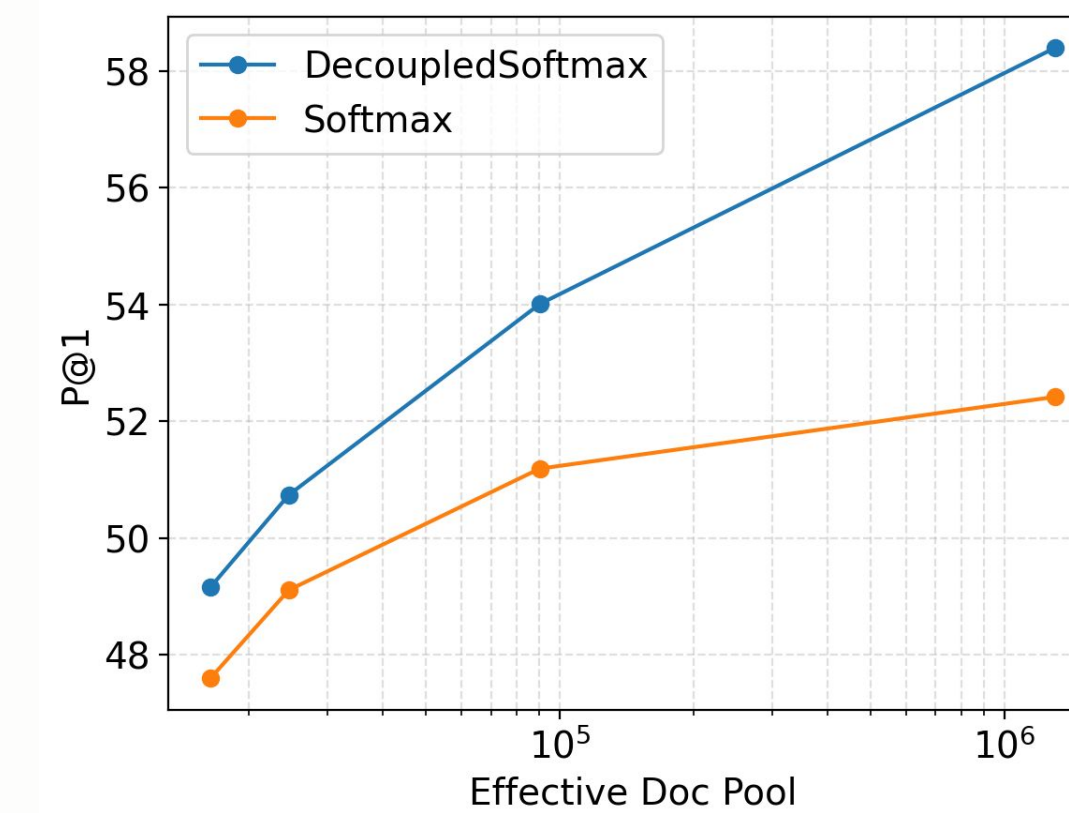
- Optimized when each positive get equal probability
- All probabilities sum upto 1
- Not all labels equally easy!

DecoupledSoftmax and SoftTop-k

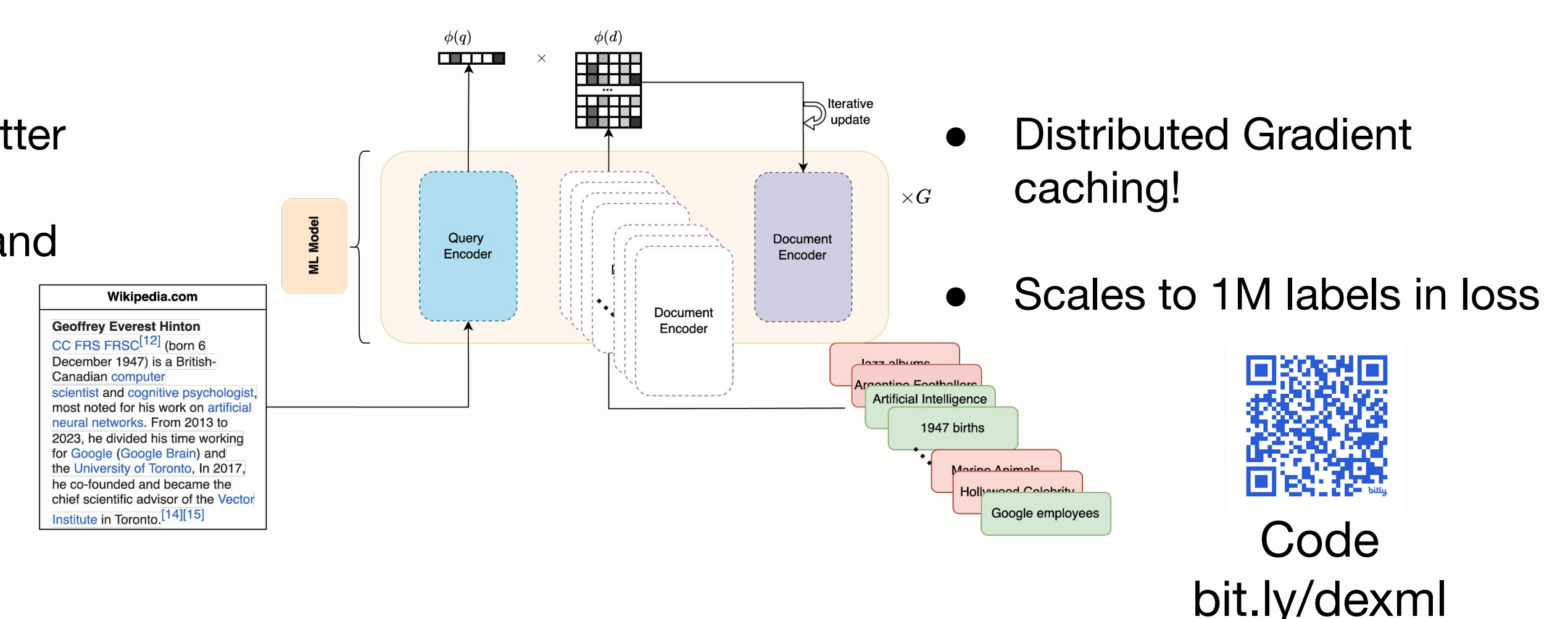


- Decouples probabilities of positives from each other
- Generalize softmax to allow probabilities to sum to given k
- Useful in top-k retrieval

Scaling Challenges



- More labels in loss computation better
- But incurs large memory footprint and computationally expensive



Code
bit.ly/dexml

Results

LF-AmazonTitles-1.3M

Method	Params	P@1	P@5
XR-Transformer	3B	50.14	39.98
ELIAS	1B	49.26	39.29
NGAME	1B	56.75	44.09
DEXA	1B	56.63	43.90
DEXML (ours)	66M	58.40	45.46

Loss ablation (EURLex-4K)

Loss	P@1	P@5	R@100
BCE	0.1	0.07	1.84
Softmax	80.05	58.36	92.57
DecoupledSoftmax	86.78	60.19	91.75
SoftTop-5	83.42	60.95	91.30
SoftTop-100	52.34	37.41	93.72

Conclusions

- Showed dual-encoders are performant on XMC tasks
 - Parameter-efficient and generalizable approach for XMC
 - Universally applicable solutions for all retrieval setting
- Showed existing DE train losses not appropriate for multi-label setting
- DecoupledSoftmax and SoftTop-k, which overcomes limitations
- Applicable in multi-document retrieval augmented generation (RAG)