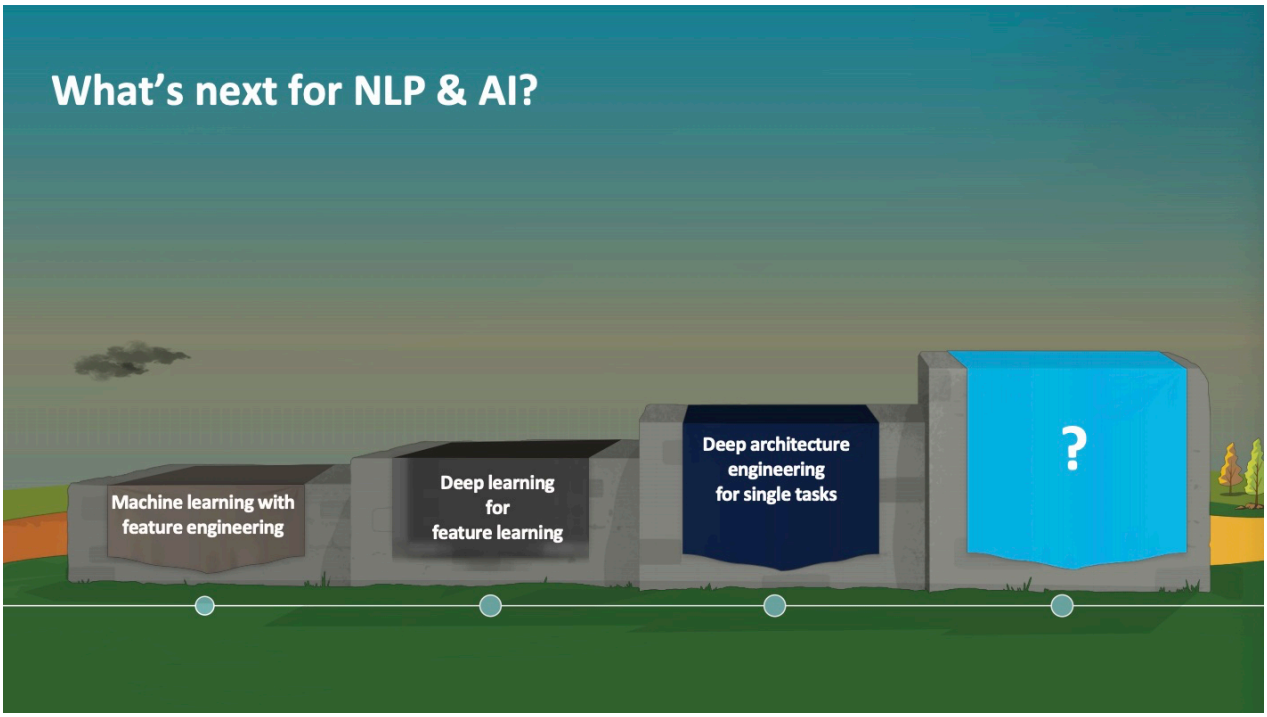
Lecture 17 Multitask Learning

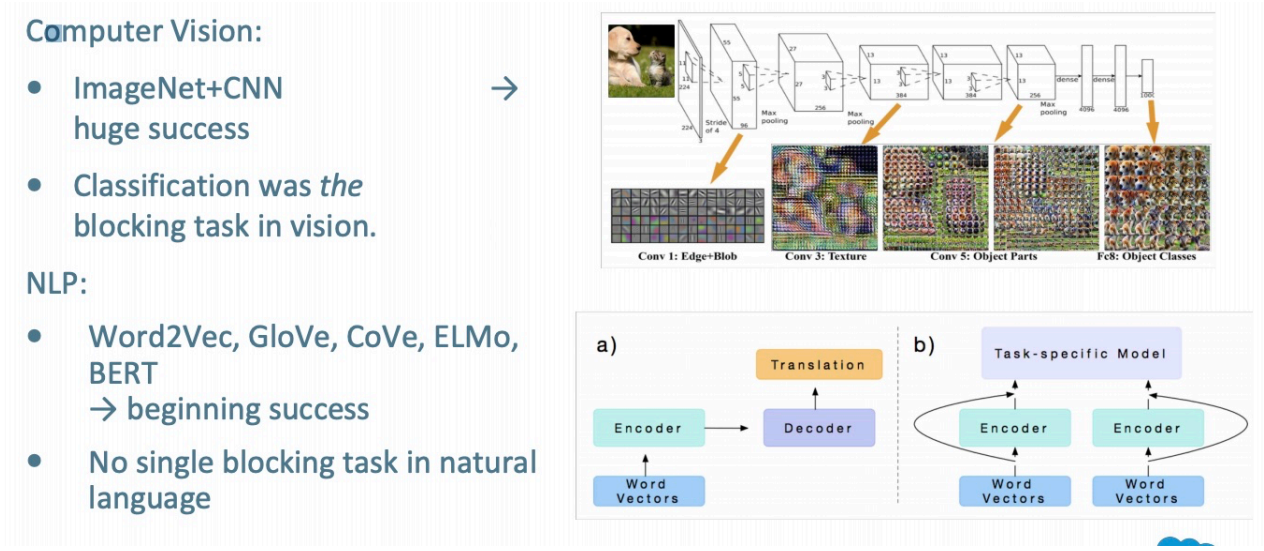
The Natural Language Decathlon: Multitask Learning as Question Answering



The Limits of Single-task Learning

- 鉴于{dataset，task，model，metric}，近年来性能得到了很大改善
- 只要 $|\text{dataset}| > 1000 \times C$，我们就可以得到当前的最优结果 (C是输出类别的个数)
- 对于更一般的 AI，我们需要在单个模型中继续学习
- 模型通常从随机开始，仅部分预训练 😞

Pre-training and sharing knowledge is great!



Why has weight & model sharing not happened as much in NLP?

- NLP需要多种推理：逻辑，语言，情感，视觉，++

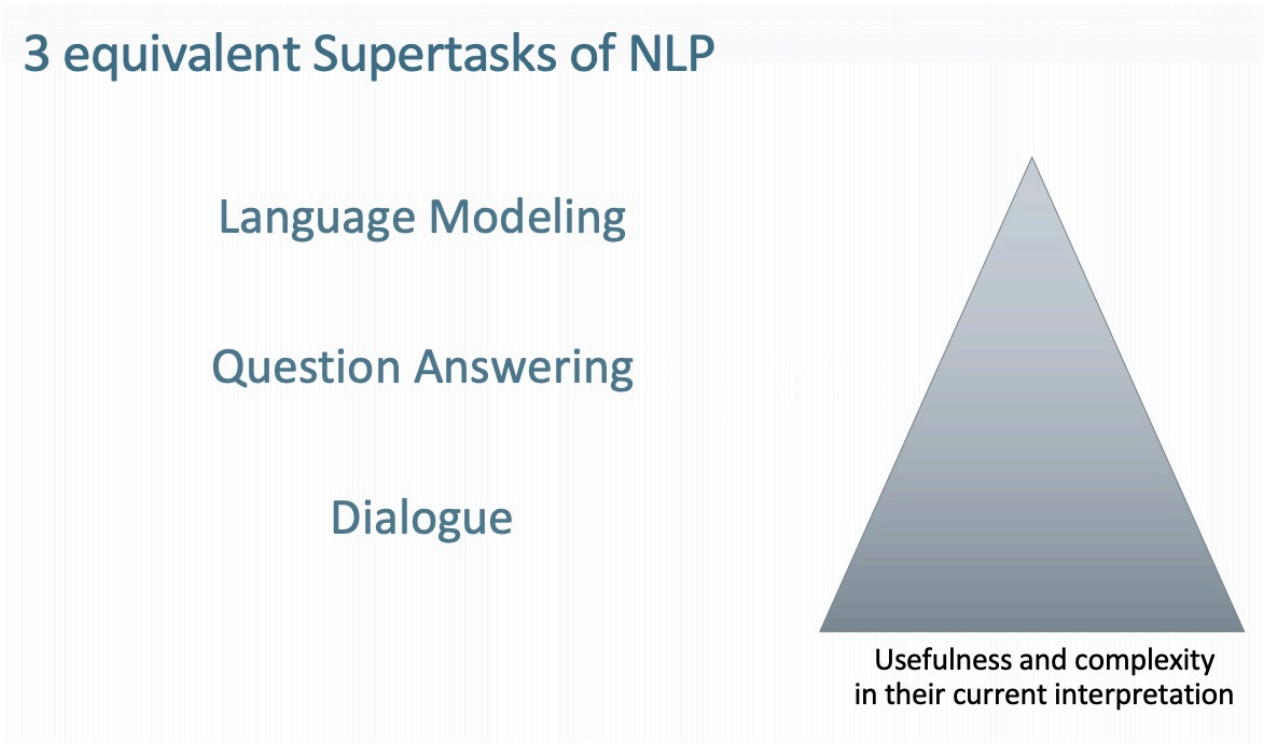
- 需要短期和长期记忆
- NLP被分为中间任务和单独任务以取得进展
    - 在每个社区中追逐基准
- 一个无人监督的任务可以解决所有问题吗？不可以
- 语言显然需要监督

Why a unified multi-task model for NLP?

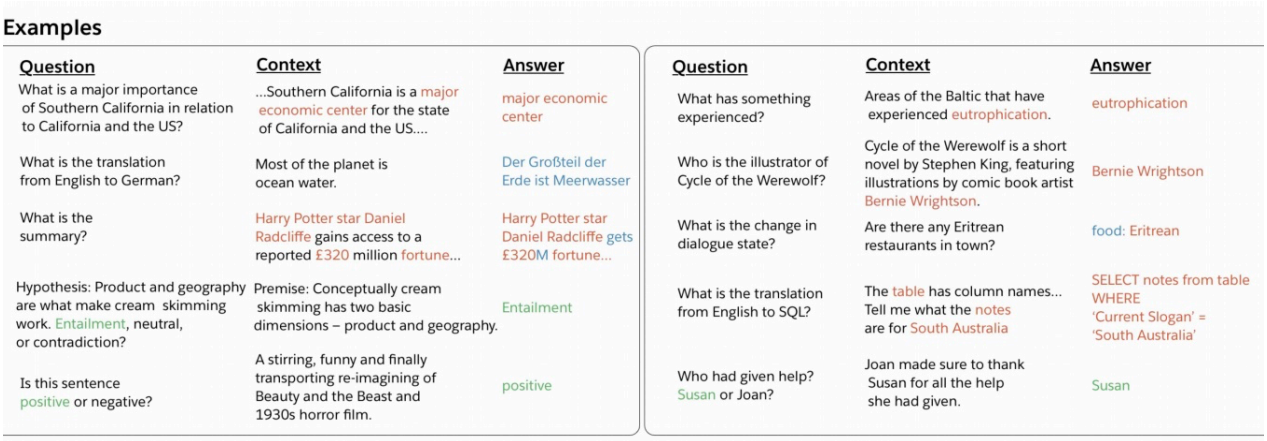
- 多任务学习是一般NLP系统的阻碍
- 统一模型可以决定如何转移知识（领域适应，权重分享，转移和零射击学习）
- 统一的多任务模型可以
    - 更容易适应新任务
    - 简化部署到生产的时间
    - 降低标准，让更多人解决新任务
    - 潜在地转向持续学习

How to express many NLP tasks in the same framework?

- 序列标记
    - 命名实体识别，aspect specific sentiment
- 文字分类
    - 对话状态跟踪，情绪分类
- Seq2seq
    - 机器翻译，总结，问答



The Natural Language Decathlon (decaNLP)



- 把 10 项不同的任务都写成了 QA 的形式，进行训练与测试

Multitask Learning as Question Answering

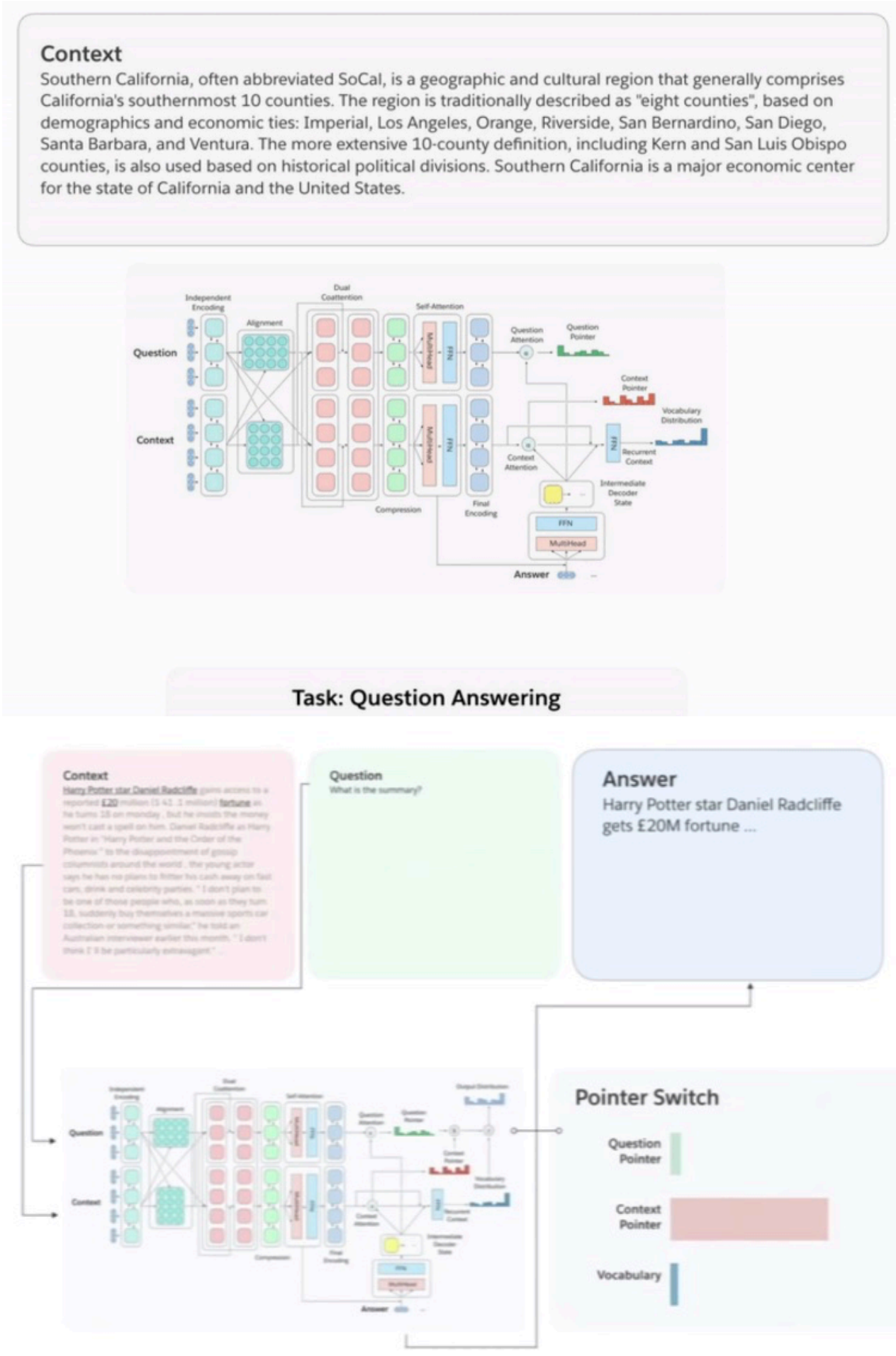
- Meta-Supervised learning 元监督学习： $\text{From } \{x, y\} \text{ to } \{x, t, y\} (t \text{ is the task})$
- 使用问题 q 作为任务 t 的自然描述，以使模型使用语言信息来连接任务
- y 是 q 的答案，x 是回答 q 所必需的上下文

Designing a model for decaNLP

需求：

- 没有任务特定的模块或参数，因为我们假设任务ID是未提供的
- 必须能够在内部进行调整以执行不同的任务
- 应该为看不见的任务留下零射击推断的可能性

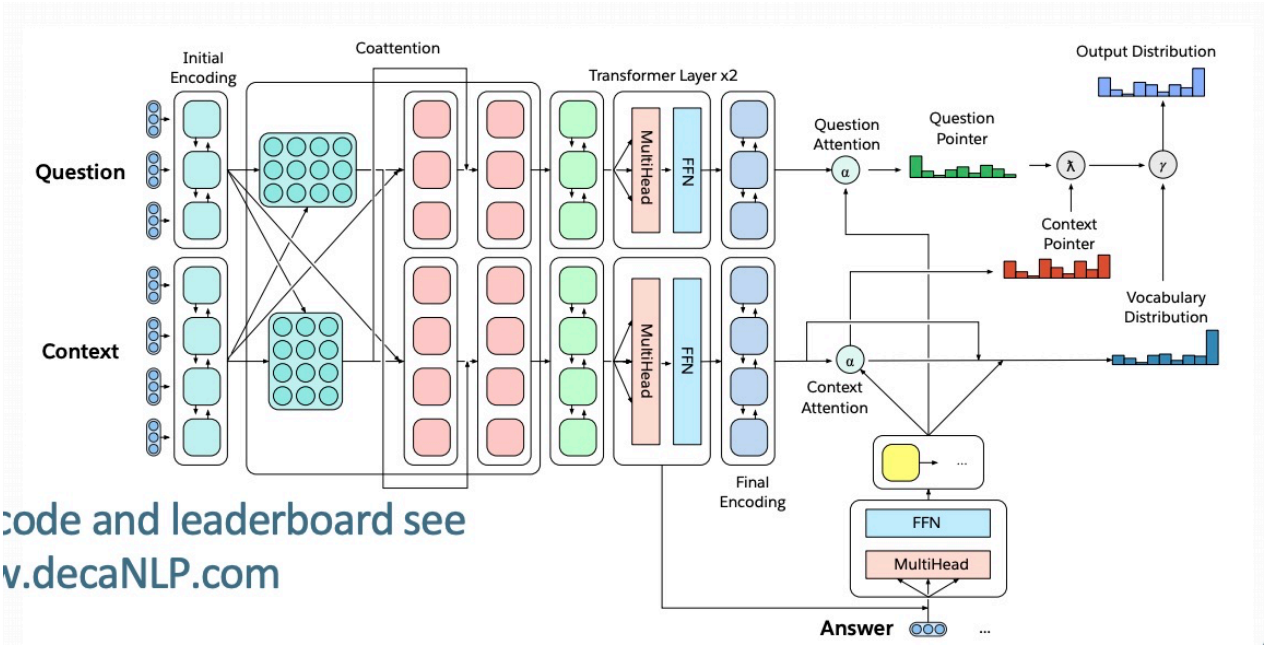
A Multitask Question Answering Network for decaNLP


Context
Southern California, often abbreviated SoCal, is a geographic and cultural region that generally comprises California's southernmost 10 counties. The region is traditionally described as "eight counties", based on demographics and economic ties: Imperial, Los Angeles, Orange, Riverside, San Bernardino, San Diego, Santa Barbara, and Ventura. The more extensive 10-county definition, including Kern and San Luis Obispo counties, is also used based on historical political divisions. Southern California is a major economic center for the state of California and the United States.
Question
Context
Independent Encoding
Alignment
Dual Coattention
Compression
Self-Attention
Final Encoding
Question Attention
Question Pointer
Context Pointer
Vocabulary Distribution
Context Attention
Recurrent Context
Intermediate Decoder State
FFN
MultiHead
Answer
Task: Question Answering
Context
Question
What is the summary?
Answer
Harry Potter star Daniel Radcliffe gets £20M fortune ...
Pointer Switch
Question Pointer
Context Pointer
Vocabulary

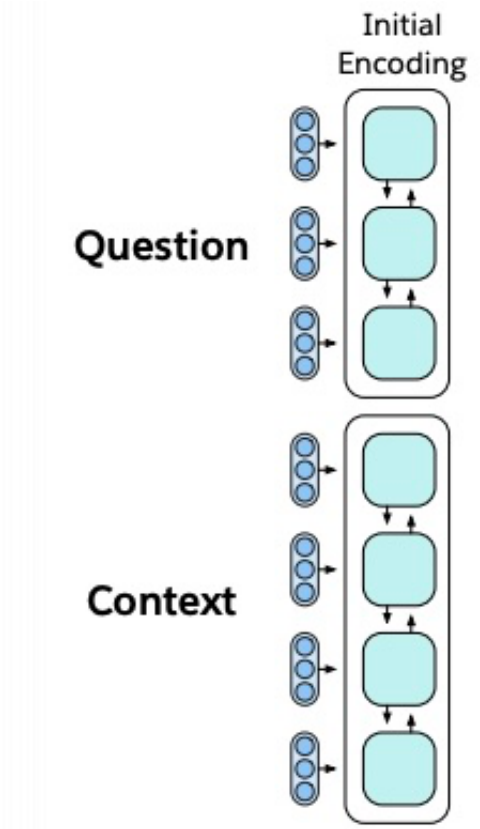
- 以一段上下文开始

- 问一个问题
- 一次生成答案的一个单词，通过
  - 指向上下文
  - 指向问题
  - 或者从额外的词汇表中选择一个单词
- 每个输出单词的指针切换都在这三个选项中切换

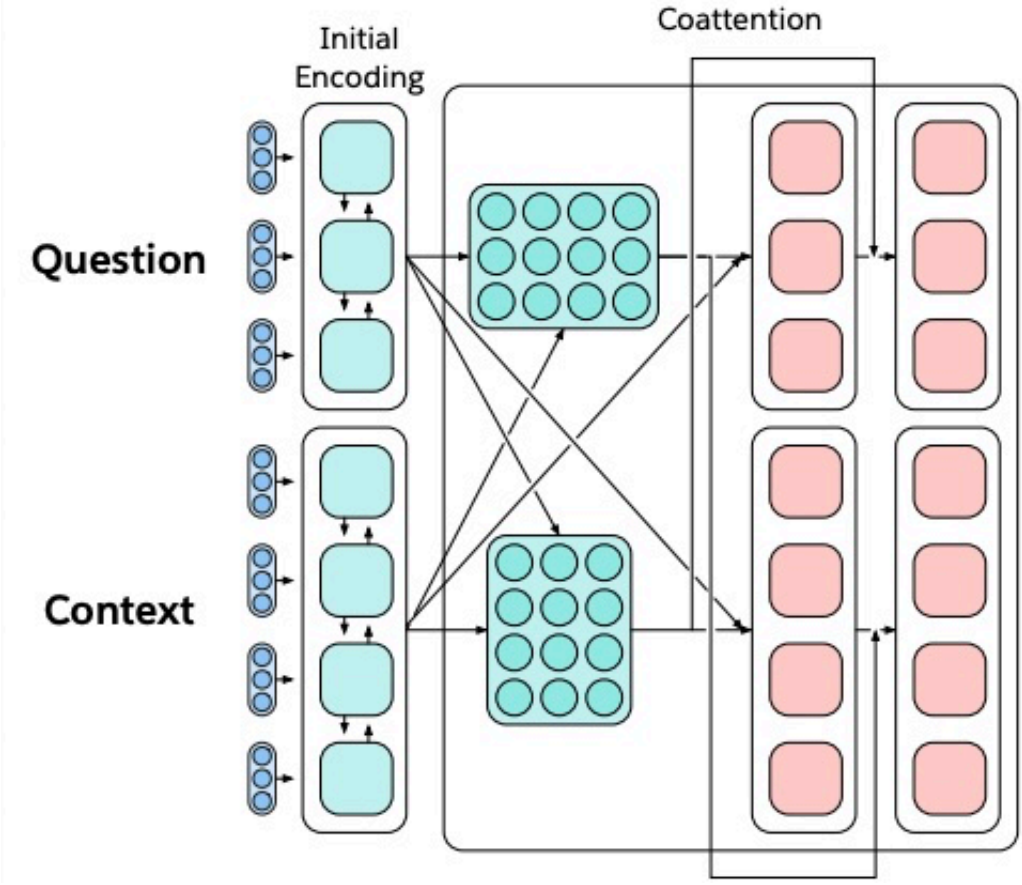
Multitask Question Answering Network (MQAN)



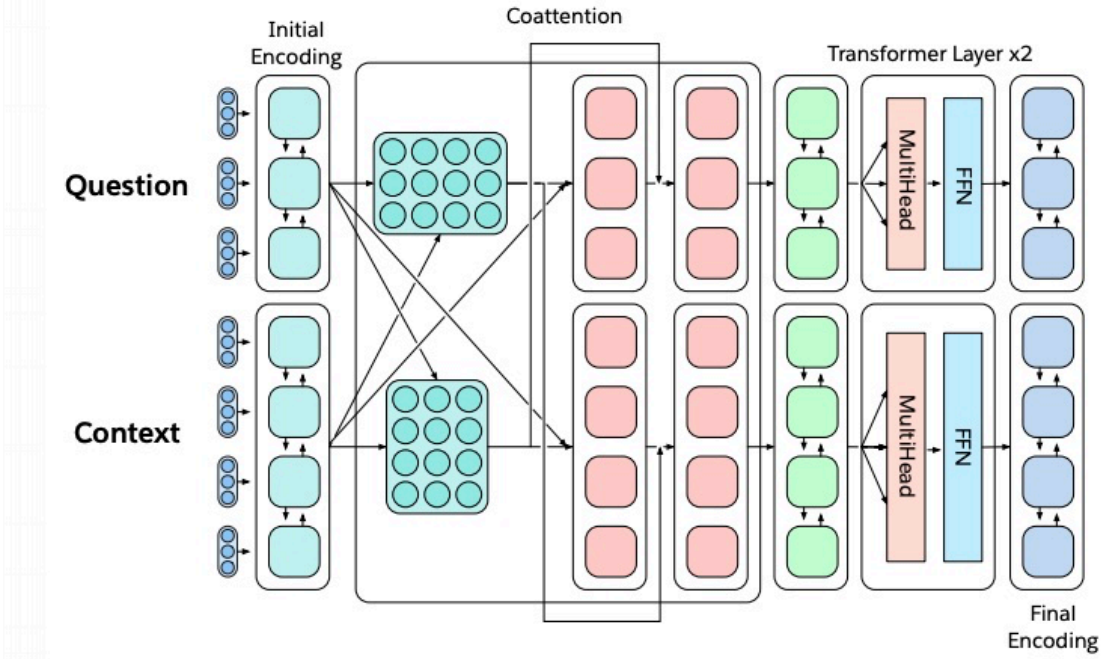
- For code and leaderboard see www.decaNLP.com
- 固定的 GloVe 词嵌入 + 字符级的 n-gram 嵌入 $\rightarrow$ Linear $\rightarrow$ Shared BiLSTM with skip connection



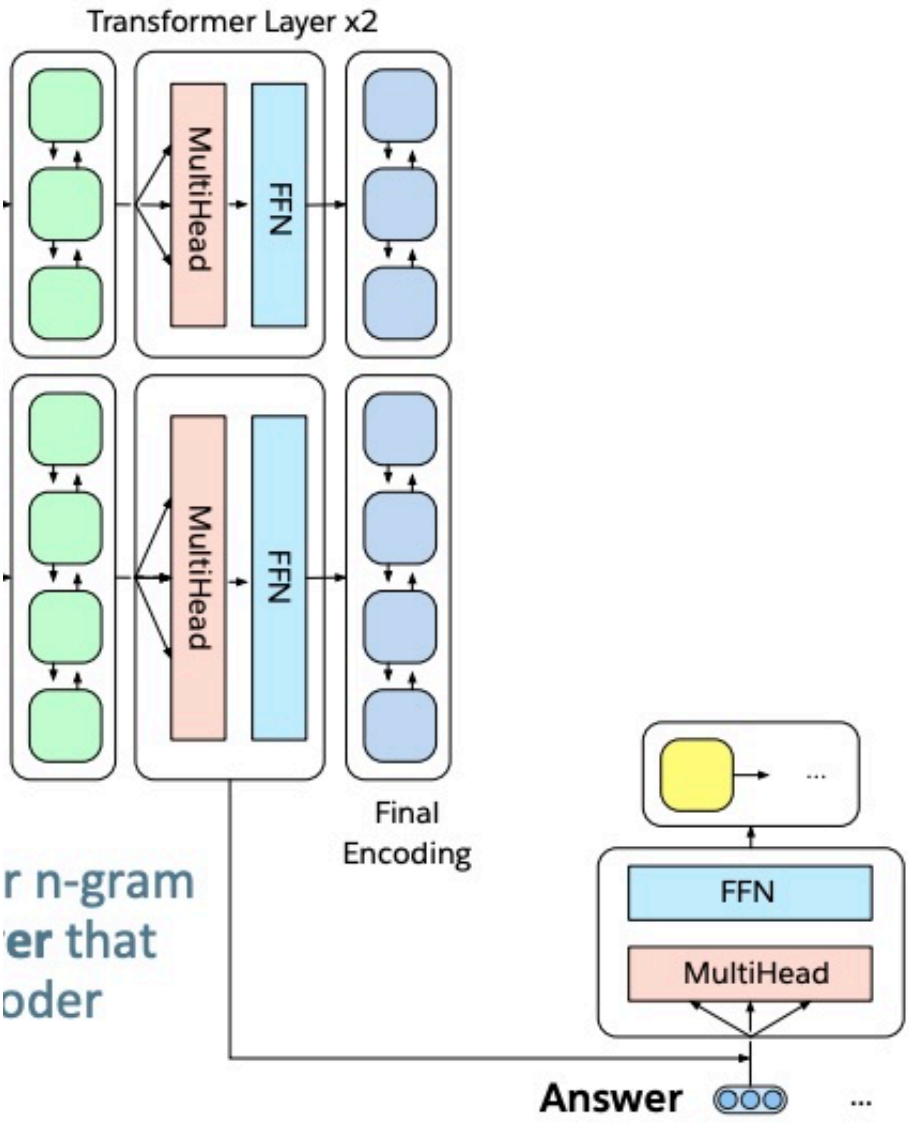
- 从一个序列到另一个序列的注意力总结，并通过跳过连接再次返回



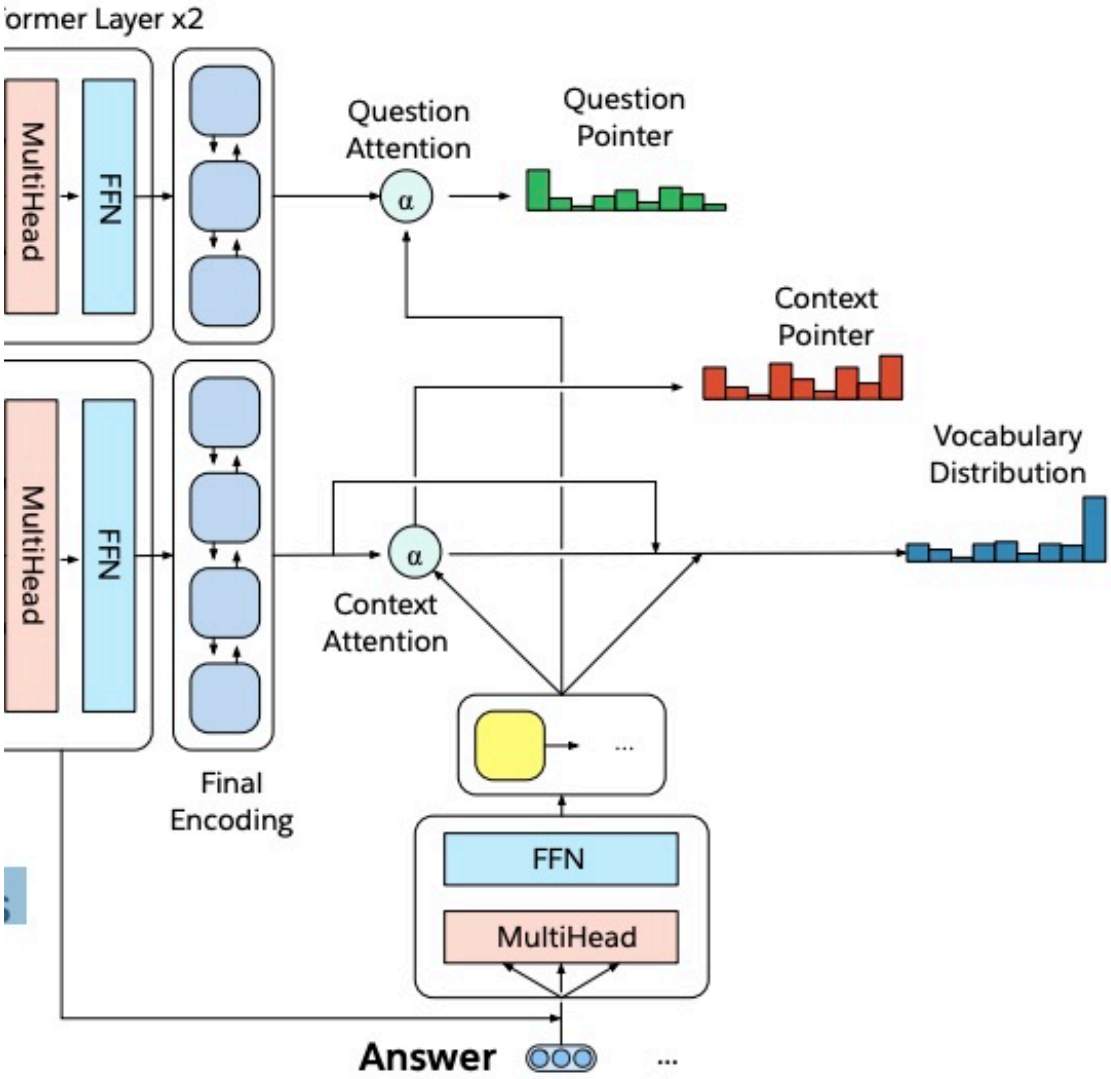
- 分离BiLSTM以减少维数，两个变压器层，另一个BiLSTM



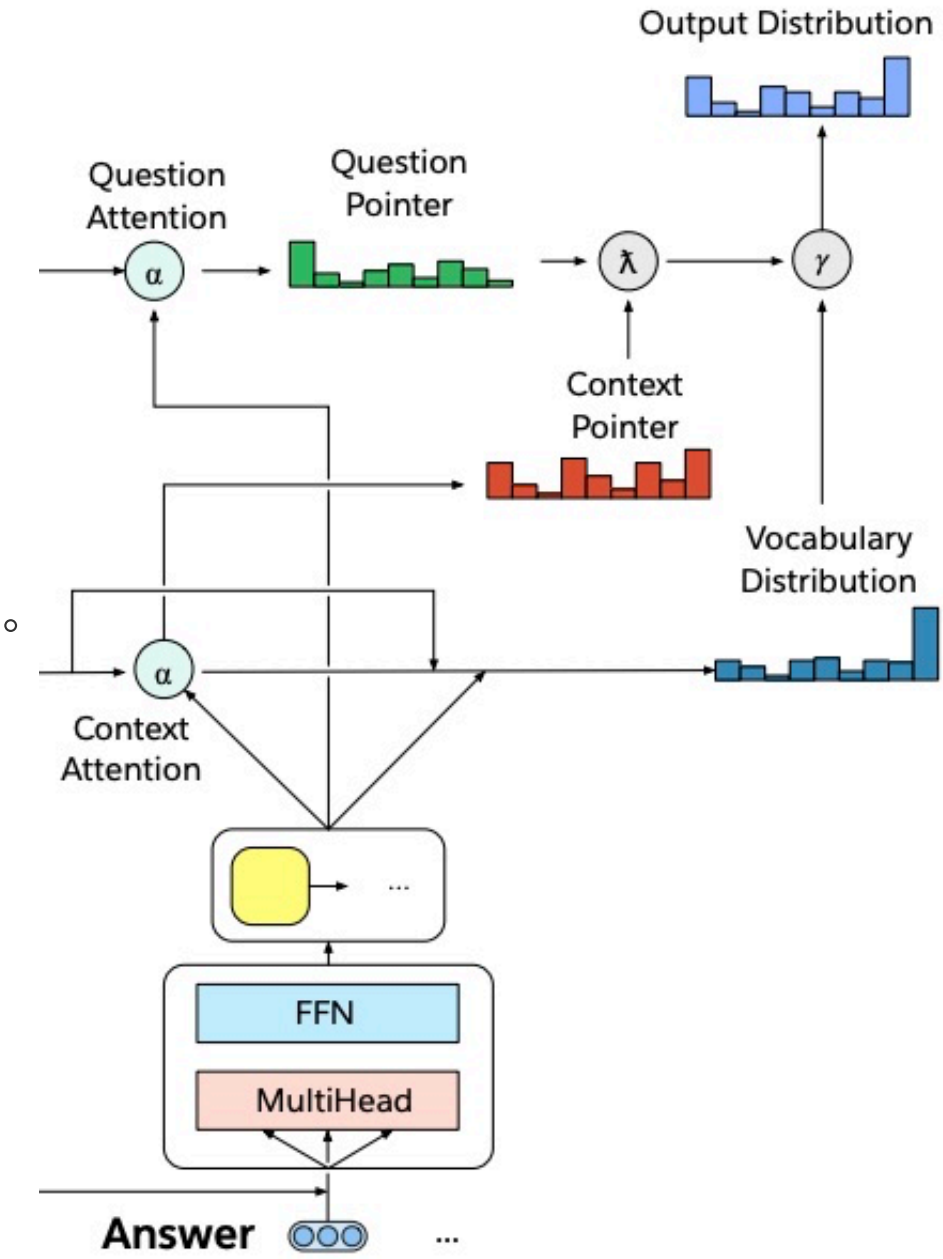
- 自回归解码器使用固定的 GloVe 和字符 n-gram 嵌入，两个变压器层和一个LSTM层来参加编码器最后三层的输出



- LSTM解码器状态用于计算上下文与问题中的被用作指针注意力分布问题



- 对上下文和问题的关注会影响两个**开关**：
  - gamma决定是复制还是从外部词汇表中选择
  - lambda决定是从上下文还是在问题中复制



Evaluation	Dataset	Metric
Question Answering	SQuAD	nF1
Machine Translation	IWSLT En — De	BLEU
Summarization	CNN/DailyMail	ROUGE
Natural Language Inference	MultiNLI	EM
Sentiment Analysis	SST2	EM
Semantic Role Labeling	QA-SRL	nF1
Relation Extraction	QA-ZRE	cF1
Goal-Oriented Dialogue	WOZ	dsEM
Semantic Parsing	WikiSQL	lfEM
Pronoun Resolution	Winograd Schemas	EM

nF1 = normalized word-level F1
(case insensitive , no punctutation or articles)
ROUGE = average of ROUGE-1, 2, and L
EM = exact match

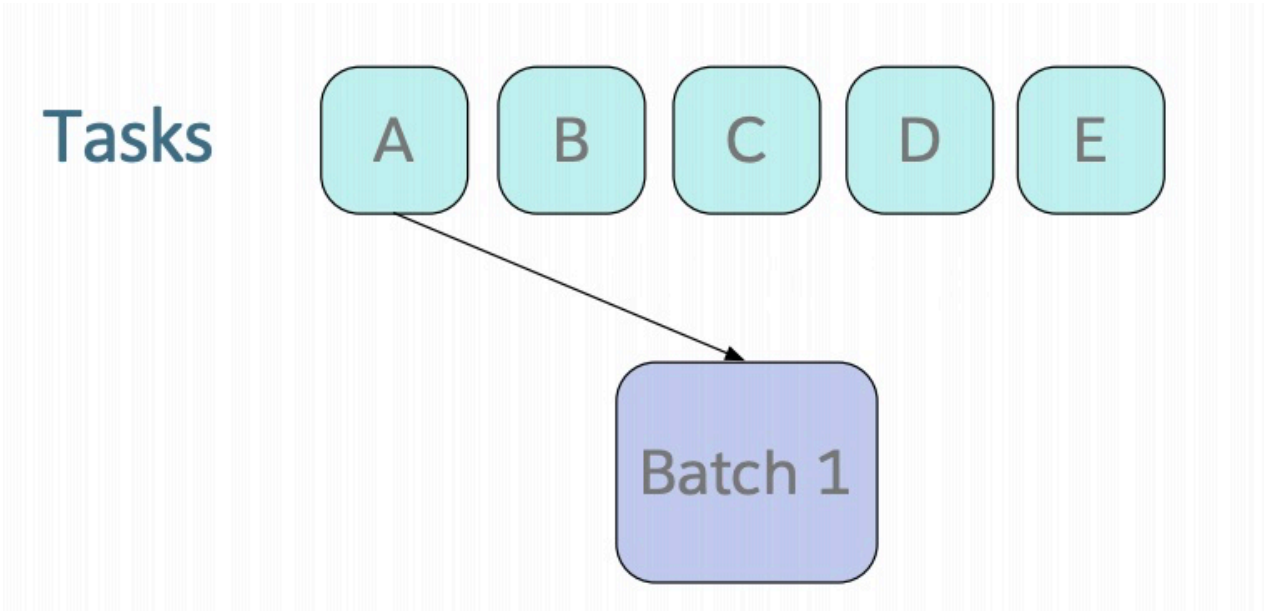
cF1 = corpus-level F1
(accounts for unanswerable questions)
dsEM = dialogue state EM
lfEM = logical form EM

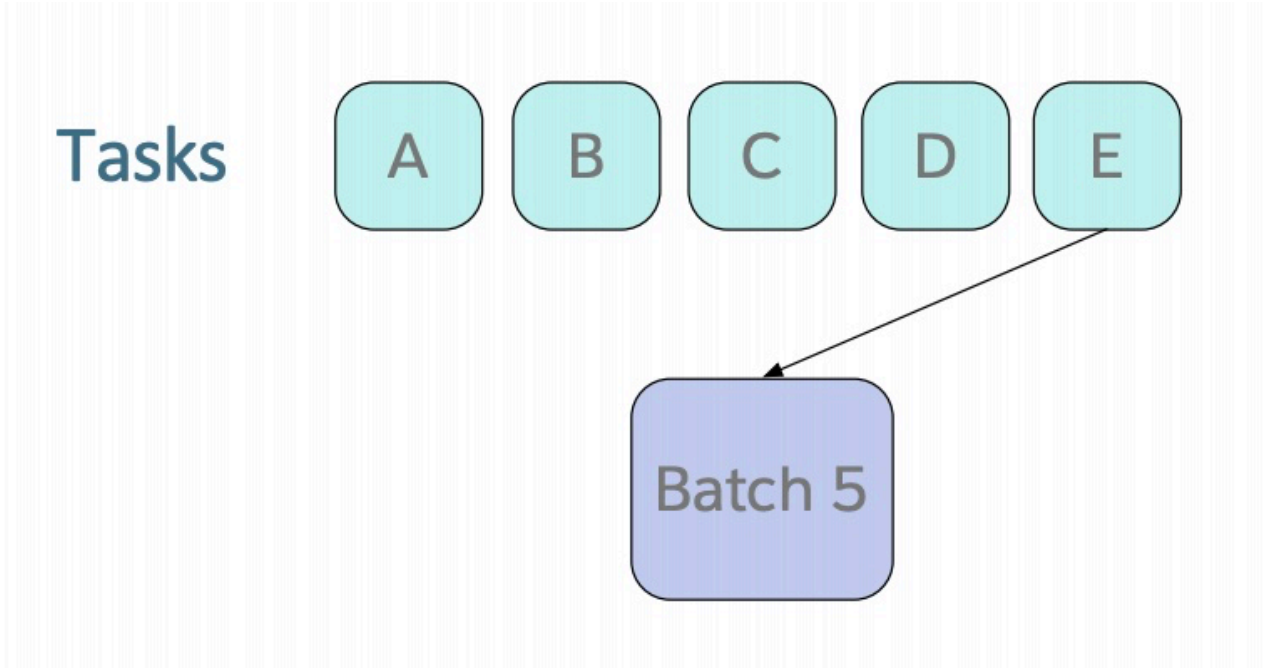
	Single-task Performance				Multitask Performance			
Dataset	S2S	+SelfAtt	+CoAtt	+QPtr	S2S	+SelfAtt	+CoAtt	+QPtr
SQuAD	48.2	68.2	74.6	75.5	47.5	66.8	71.8	70.8
IWSLT En — De	25.0	23.3	26.0	25.5	14.2	13.6	9.00	16.1
CNN/DailyMail	19.0	20.0	25.1	24.0	25.7	14.0	15.7	23.9
MultiNLI	67.5	68.5	34.7	72.8	60.9	69.0	70.4	70.5
SST2	86.4	86.8	86.2	88.1	85.9	84.7	86.5	86.2
QA-SRL	63.5	67.8	74.8	75.2	68.7	75.1	76.1	75.8
QA-ZRE	20.0	19.9	16.6	15.6	28.5	31.7	28.5	28.0
WOZ	85.3	86.0	86.5	84.4	84.0	82.8	75.1	80.6
WikiSQL	60.0	72.4	72.3	72.6	45.8	64.8	62.9	62.0
Winograd Schemas	43.9	46.3	40.4	52.4	52.4	43.9	37.8	48.8
decaScore					513.6	546.4	533.8	562.7

- S2S 是 seq2seq
- +SelfAtt = plus self attention
- +CoAtt = plus coattention
- +QPtr = plus question pointer == MQAN
- Transformer 层在单任务和多任务设置中有 收益
- 多任务训练一开始会获得很差的效果（干扰和遗忘），但是如果顺序训练这些任务，将很快就会好起来
- QA和SRL有很强的关联性
- 指向问题至关重要
- 多任务处理有助于实现零射击
- 组合的单任务模型和单个多任务模型之间存在差距

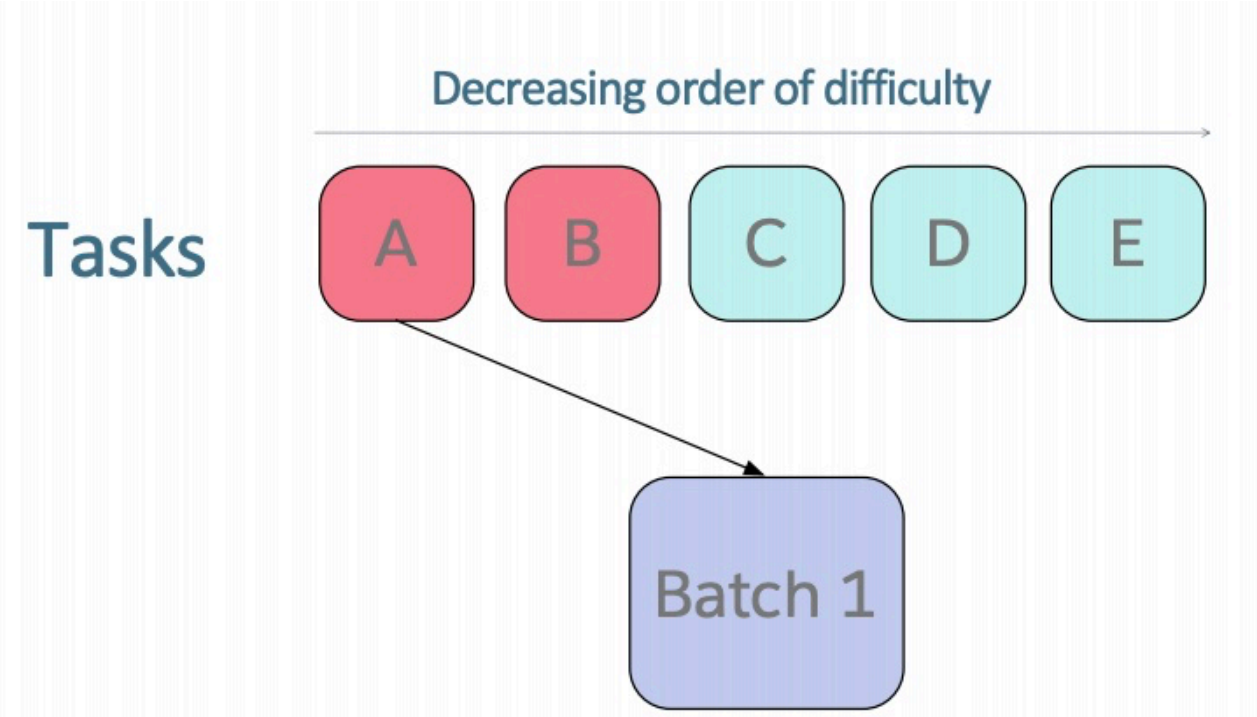
Training Strategies: Fully Joint

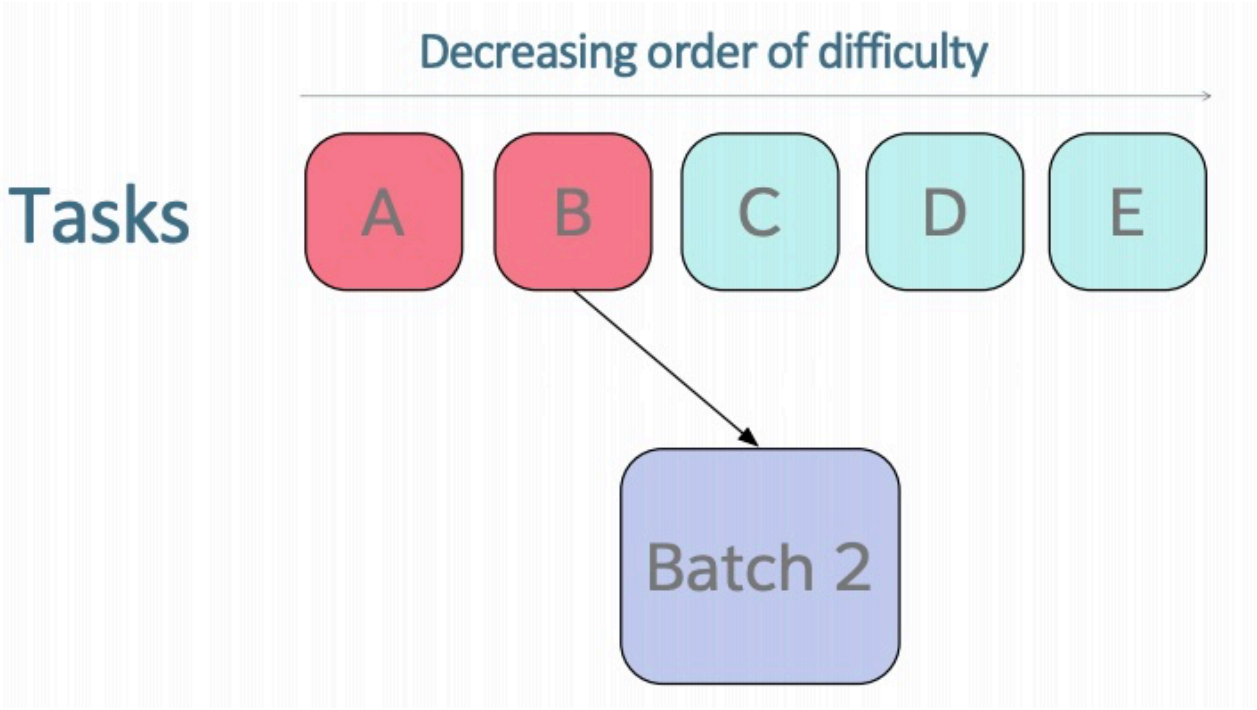
简单的全联合训练策略

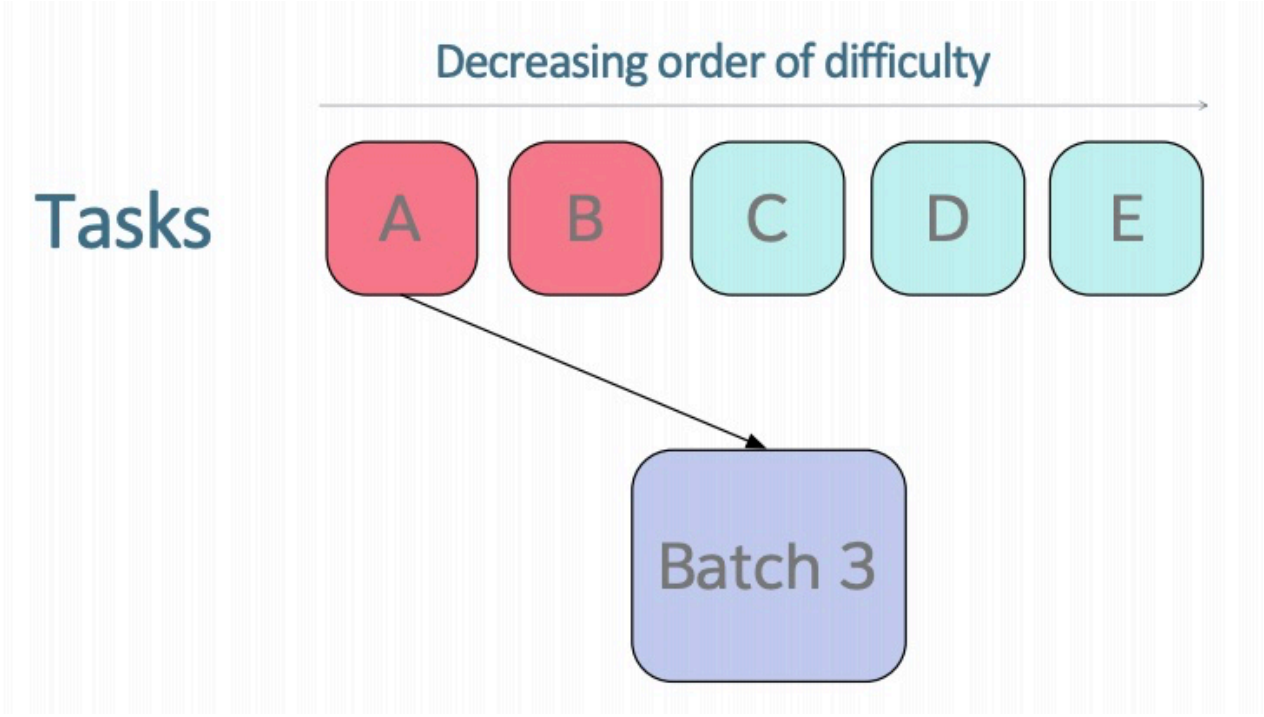


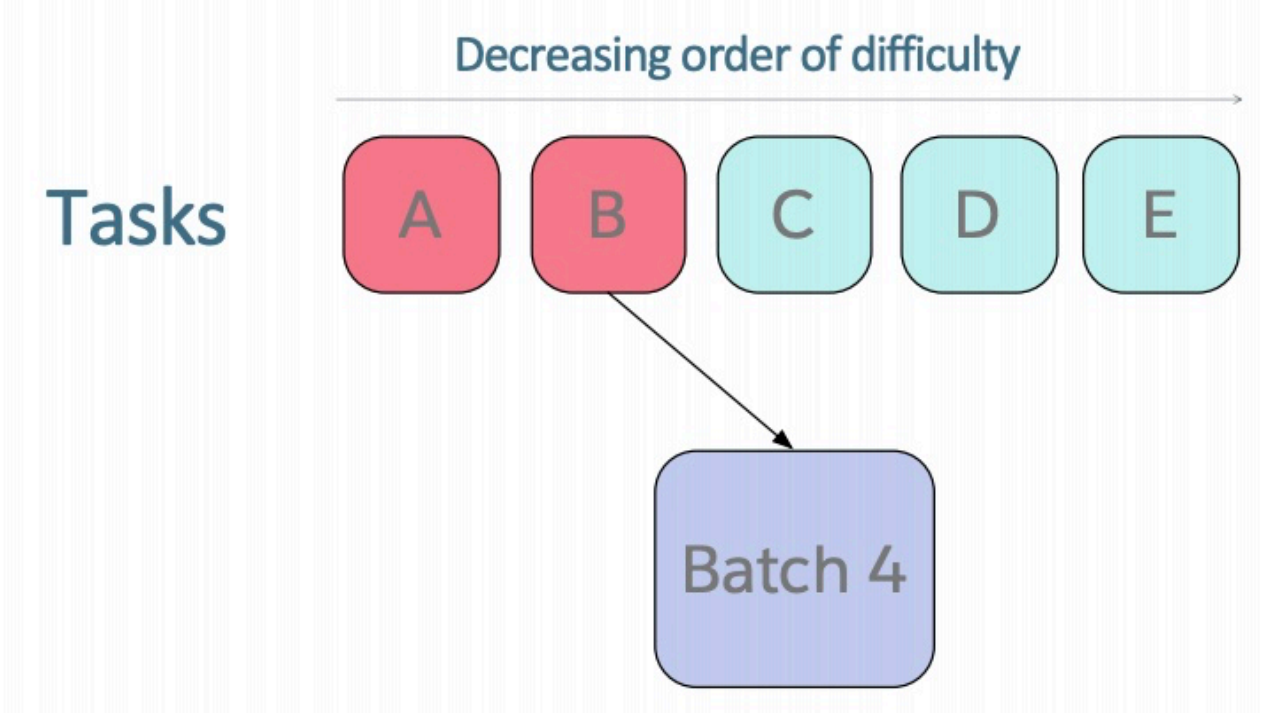


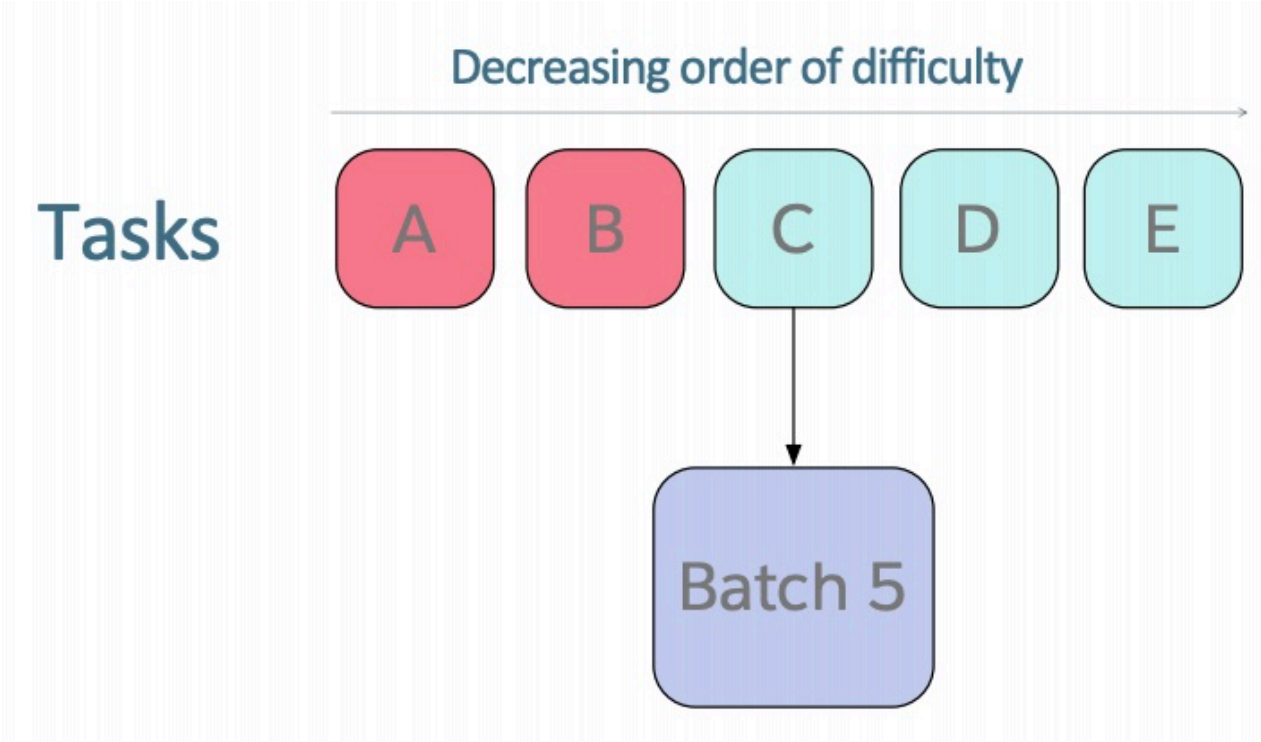
Training Strategies: Anti-Curriculum Pre-training


Decreasing order of difficulty
Tasks
A
B
C
D
E
Batch 1


Decreasing order of difficulty
Tasks
A
B
C
D
E
Batch 2


Decreasing order of difficulty
Tasks
A
B
C
D
E
Batch 3


Decreasing order of difficulty
Tasks
A
B
C
D
E
Batch 4



- 困难：在单任务设置中收敛多少次迭代
- 带红色的任务：预训练阶段包含的任务
- QA 的 Anti-curriculum 反课程预训练改进了完全联合培训
- 但MT仍然很糟糕

Closing the Gap: Some Recent Experiments

MQAN at ~563 with fully joint training, Set of Single Models (SOSM) started at 586.1
-- the gap started at 23

MQAN at ~571 with anti-curriculum training (SQuAD pre-training)
--dropped the gap to 15.

MQAN at~593 and BOSM ~618 with CoVe
--increased the gap from 15 to 25, but raised overall performance

MQAN at ~609 by including more tasks in the first phase of anti-curriculum pretraining
-- dropped the gap to about 5 points.

MQAN at ~617 by oversampling on IWSLT
--dropped the gap to 1 point

	Single-task Performance					Multitask Performance					
Dataset	S2S	+SelfAtt	+CoAtt	+QPtr	+CoVe	S2S	+SelfAtt	+CoAtt	+QPtr	+ACurr	+Cove+Tune
SQuAD	48.2	68.2	74.6	75.5	77.2	47.5	66.8	71.8	70.8	74.3	77.1
IWSLT En – De	25.0	23.3	26.0	25.5	28.2	14.2	13.6	9.00	16.1	13.7	21.4
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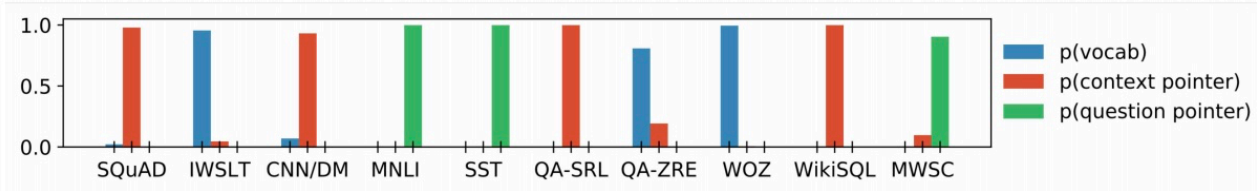
SST2	86.4	86.8	86.2	88.1	88.2	85.9	84.7	86.5	86.2	86.4	87.0
QA-SRL	63.5	67.8	74.8	75.2	79.2	68.7	75.1	76.1	75.8	77.6	80.4
QA-ZRE	20.0	19.9	16.6	15.6	27.0	28.5	31.7	28.5	28.0	34.7	47.0
WOZ	85.3	86.0	86.5	84.4	89.2	84.0	82.8	75.1	80.6	84.1	86.9
WikiSQL	60.0	72.4	72.3	72.6	73.0	45.8	64.8	62.9	62.0	58.7	69.7
Winograd Schemas	43.9	46.3	40.4	52.4	53.7	52.4	43.9	37.8	48.8	48.4	49.6
decaScore				(586.1)	(618.2)	513.6	546.4	533.8	562.7	571.7	616.8

Where MQAN Points



- 答案从上下文或问题中正确的复制
- 没有混淆模型应该执行哪个任务或使用哪个输出空间

Pretraining on decaNLP improves final performance

- 例如额外的 IWSLT language pairs
- 或者是新的类似 NER 的任务

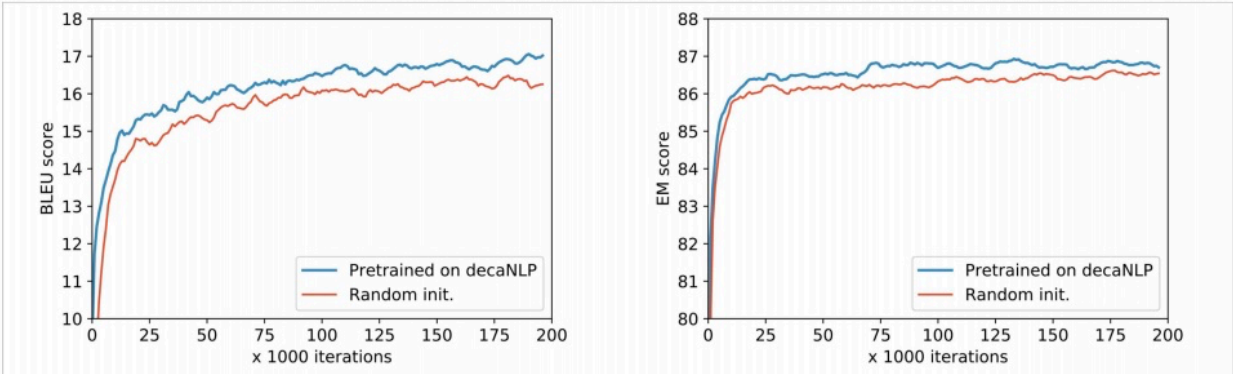


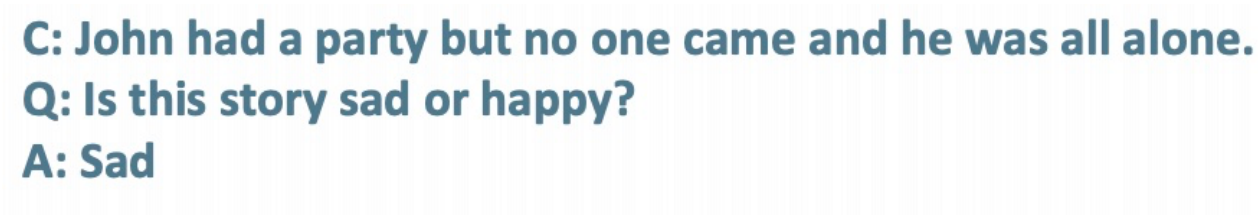
Figure 4: MQAN pretrained on decaNLP outperforms random initialization when adapting to new domains and learning new tasks. Left: training on a new language pair – English to Czech, right: training on a new task – Named Entity Recognition (NER).

Zero-Shot Domain Adaptation of pretrained MQAN:

- 在 Amazon and Yelp reviews 上获得了 80% 的 精确率
- 在 SNLI 上获得了 62% （参数微调的版本获得了 87% 的精确率，比使用随机初始化的高 2%）

Zero-Shot Classification

- 问题指针使得我们可以处理问题的改变（例如，将标签转换为满意/支持和消极/悲伤/不支持）而无需任何额外的微调
- 使模型无需训练即可响应新任务



decaNLP: A Benchmark for Generalized NLP

- 为多个NLP任务训练单问题回答模型
- 解决方案
    - 更一般的语言理解
    - 多任务学习
    - 领域适应
    - 迁移学习
    - 权重分享，预训练，微调（对于NLP的ImageNet-CNN？）
    - 零射击学习

https://einstein.ai

Reference

以下是学习本课程时的可用参考书籍：

《基于深度学习的自然语言处理》（车万翔老师等翻译）

《神经网络与深度学习》

以下是整理笔记的过程中参考的博客：

斯坦福CS224N深度学习自然语言处理2019冬学习笔记目录 (课件核心内容的提炼，并包含作者的见解与建议)

斯坦福大学 CS224n自然语言处理与深度学习笔记汇总 {>>这是针对note部分的翻译<<}