Position-wise Feed-Forward Networks

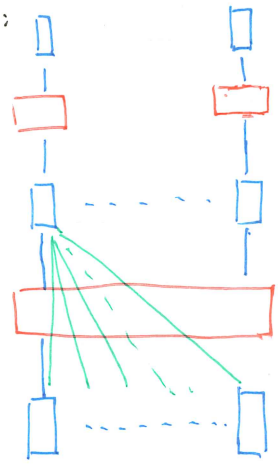
- Applied to each position separately and identically

$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

W_1: project to $d = 2048$ 输入扩大四倍(中间隐藏层)

W_2: project back to $d = 512$

Transformer:



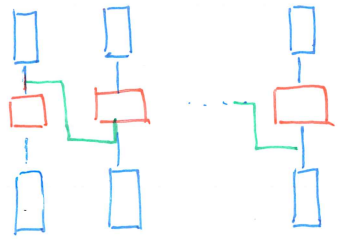
MLP 增强信息活化能力，在抽象层面表示更多，映射成我更想要的语义空间

single MLP 即可，历史信息已被汇聚

(全局)

抓取序列中信息，并做汇聚 (aggregation)

RN



时序信息来自上一时刻

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Embedding

We use learned embeddings to convert the input tokens and output tokens to vectors of d_{model} (512)

· Same weight matrix between two embedding layers and the pre-softmax linear transformation.

· multiply weights by $\sqrt{d_{model}}$ 在学embedding时L2long会比较小，乘以d以匹配Positional Encoding的scale（维度越大的向量归一化后单个值越小）

Positional Encoding.

Attention中无时序信息

$PE(pos,2i) = \sin(pos/10000^{2i/d})$

$PE(pos,2i+1) = \cos(pos/10000^{2i/d})$

用周期不同的sin和cos函数计算用来表示词的向量（d=512）

与Input embedding直接相加，两个都在[-1,1]附近

Layer Type.	Complexity / Layer	Sequential Operation (计算便利度(多少能够平行计算))	Max Path length. (learn long-range dependency) (信息整合性)
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(\log_k(n))$
Self-Attention. (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

Campus Attention缺点：需要更多数据和更大模型，贵，跑小训练集容易过拟合

Training

25000 source and target tokens.

NVIDIA P100 : 8

Base model: 0.4 sec / training step

100,000 steps

big models: 1.0 sec / training step

300,000 steps

Adam optimizer with $\beta_1 = 0.9$ $\beta_2 = 0.98$ and $\varepsilon = 10^{-9}$.

$$\text{learning rate} = d_{\text{model}}^{-0.5} \cdot \min(\text{step\_num}^{-0.5}, \text{step\_num} \cdot \text{warmup\_steps}^{-1.5})$$

4000

模型越宽向量越长，学习率越低

从小到大

爬到最高后按 0.5 次方衰减

Regularization:

① Residual Dropout. 在子层(Multi-head, MLP)的输出进入残差连接和进入 layer-alone 前做 dropout. $P_{drop} = 0.1$ → 10% 的×0，剩下 9% 乘以 $\frac{1.0}{0.9}$

在 embedding 与 positional encoding 之后也 dropout 0.1

② Label smoothing: 对于正确的词 softmax 只需到 0.9（实际很难逼近 1）

置信度

但会增加模型不确信度

No.

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Improving Language Understanding by Generative Pre-Training

No.
Date

generative
GPT：生在未标号（unlabeled）文件上生成一个预训练模型，再在有标号的子任务上训练分辨率的微调模型

在微调时构造任务相关（task-aware）的输入很少改变架构

Pre-trained word embedding can improve performance in many NLP tasks
词嵌入模型

困难：①. 不知道用什么优化目标函数.（optimization objectives）
各有所长

②. 难以把学到的表示传递到下游子任务上面
子任务差异大，没有统一有效的方式

Semi-supervised —— Combinations of unsupervised pretraining and supervised finetuning

架构：Transformer：

相比于RNN，transformer 在迁移学习时学到的特征更稳健（robust）

原因：Transformer 具有更结构化的记忆（structured memory）
能处理更长文本，抽取句子和段落层面的语义信息.

- 使用任务相关的输入表示

Unsupervised Pre-training

☆ To maximize the following likelihood

$$L_1(u) = \sum_i \log P(u_i | u_{i-k}, \dots, u_{i-1}; \theta)$$ 此处求和是因为log放回去就是∏

(hp) k: context window.

使用 Transformer 的解码器（只有decoder 才有掩码）

The model applies a multi-headed self-attention operation over the input context tokens followed by position-wise feed forward layers

$U = (U_{-k} \dots U_{-1})$ is the context vector of tokens,

n is the number of layers.

We: Token Embedding Matrix Wp: Position Embedding Matrix

$h_0 = UW_e + W_p$

$h_l = \text{transformer\_block}(h_{l-1}) \quad \forall i \in [1, n]$

$P(u) = \text{softmax}(h_n W_e^T)$

BERT: 做完形，用 Transformer 的编码器

GPT: 用更难的目标函数，预测未来，解码器，更高天花板

Supervised fine-tuning

dataset C: each instance consists of a sequence of input tokens $x^1, x^2 \dots x^m$ along with a label y

W_y: Linear output layer to predict y (parameter)

$P(y \mid x^1, \dots x^m) = \text{softmax}(h_l^m W_y)$

☆ To maximize the following objective.

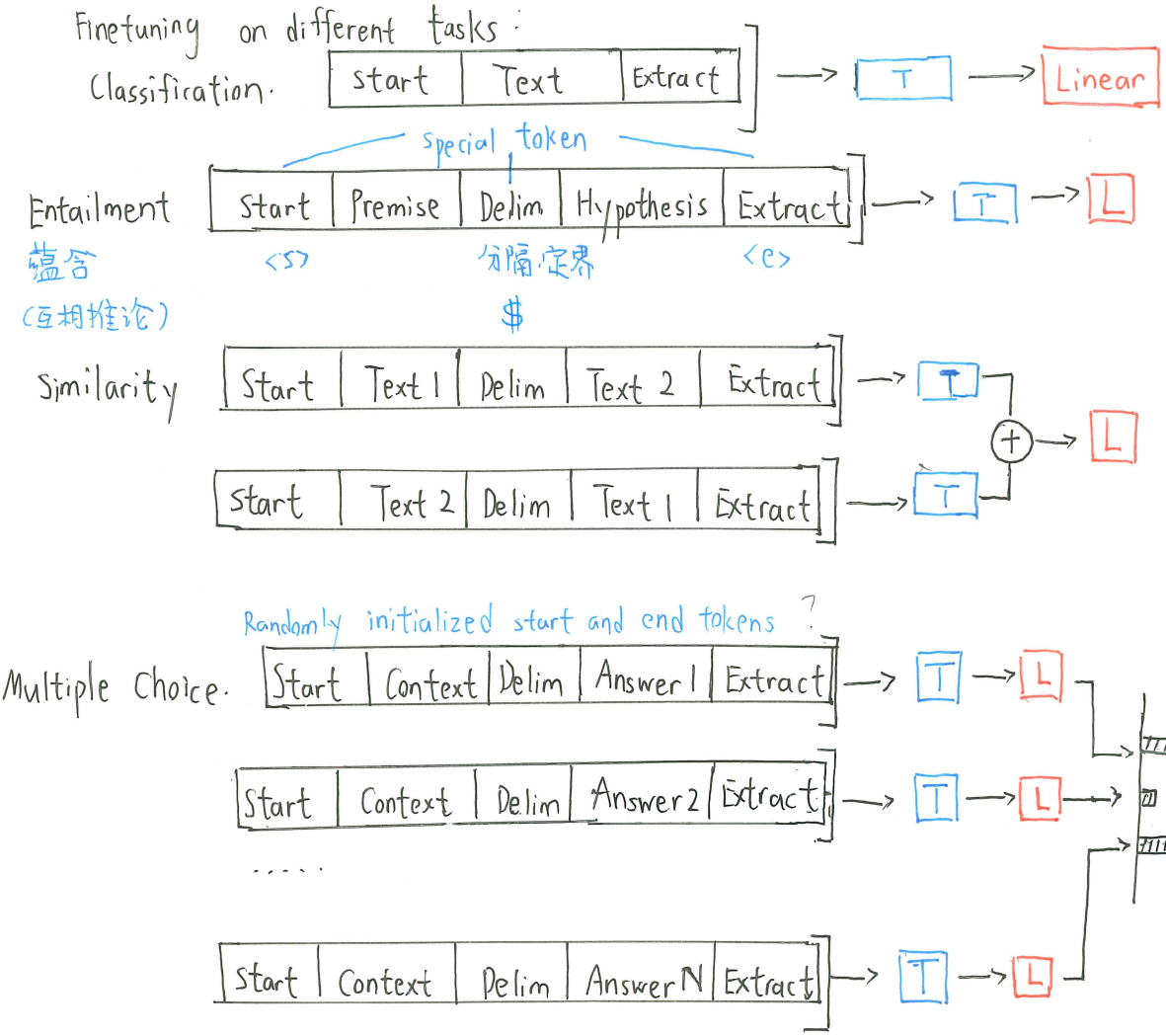
$L_2(C) = \sum_{(x,y)} \log P(y \mid x^1, \dots x^m)$

预测序列的标号

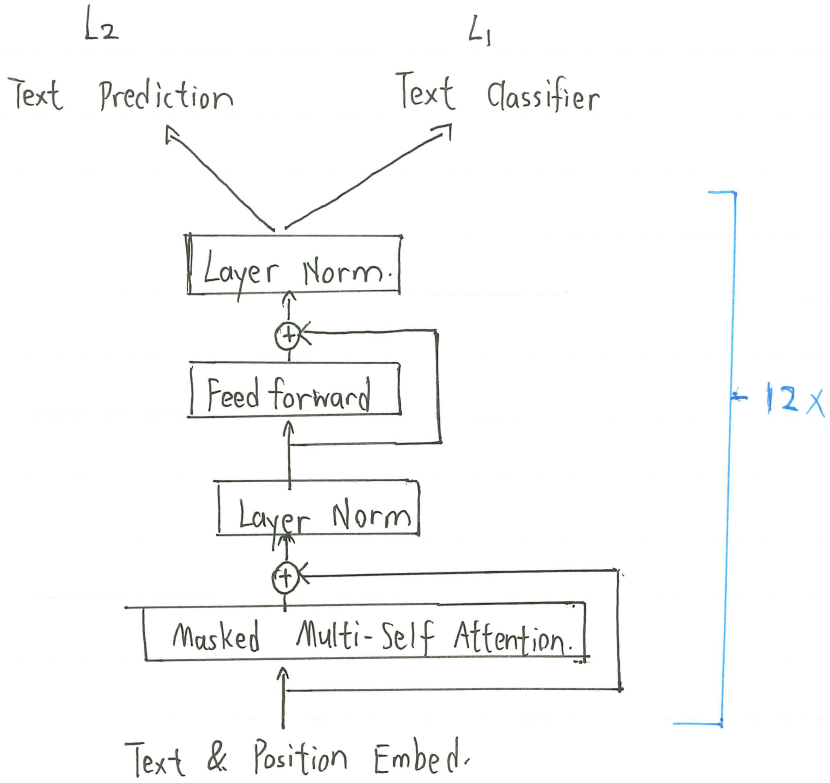
$$L_3(C) = L_2(C) + \lambda * L_1(C)$$

预测下一个词　超参

Finetuning on different tasks:

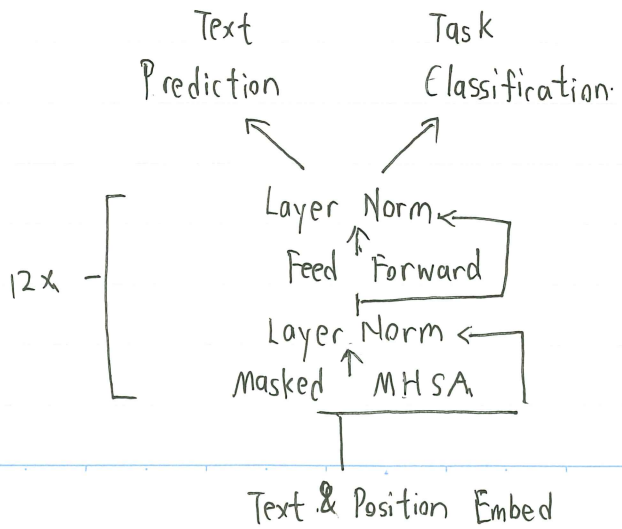


输入形式和输出构造无论怎么变，Transformer 模型不变



BERT的数据集是GPT的4倍，精度更高

GPT-2：



Language Models are Unsupervised Multitask Learners

GPT2. 数据集(wed text)

从新的角度看问题：Zero-shot，更好泛化性

Estimate conditional distribution p(output|input, task)

Language provides a flexible way to specify tasks, inputs and outputs all as a sequence of symbols.

e.g. (answer the question, document, question, answer)

whether objective is supervised doesn't influence its global minimum.

爬了reddit上 kamma>3 的数据

Difference between GPT-2 Architecture. different from the transformer model. such as.

	GPT-2	Transformer.
Decoder Layers	12	6
Attention Heads	12	8
Dimensional	768	512
Context size (for positional encoding	1024	5000.
Layer	GeLU	ReLU
Capture subwords	BytePair Encoding	Tokenization

Language Models are Few-Shot Learners

GPT 3 : 回到 Few-shot，通过大量实验。

175 billion parameters, not sparse (contain a lot of 0)

Applied without any gradient updates or fine-tuning.

微调效果好不代表大模型泛化好

* in-context learning — 在 multi task 中各任务内的上下文

无梯度更新；通过注意力机制处理长序列

Zero shot

Translate English to French: task description

cheese => prompt

One shot: task description

sea otter => butre de mer ⟶ example

prompt.

缺点：难以载入长的新训练样本

每次都要往回全部抓取。

GPT 2,3 相比于 GPT 1 的改变：① modified initialization

② : pre-normalization

③ reversible tokenization 反转词元

* 计算复杂度与宽度是平方关系，和层数是线性关系

使用相对来说大的批量：计算性能↑，并行度↑，通讯量↓。

对于小模型降低批量大小可以增加噪音

模型变大时过拟合没有那么严重，同时学习率向下减

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训练数据基于过滤后的Common Crawl ①基于GPT2数据分类过滤

② LSH算法去重（data retrieval

③ 增加高质量数据集

训练过程：分布式训练，模型分割，数据分割

局限性：文本生成新意度弱，没有推进，适合补全

2、语言生成没有重点（模型会花很多时间学虚词）。能否分类以优化？

3. 欠缺多模态

4. 样本有效性不够

5、贵

6. 决策方式未知（权重代表什么）

疑问：是基于样本学习还是在数据库中找相关？

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Principle of prompt engineering

Principle 1. Write clear and specific instructions

- To avoid prompt injections

Tactic1: Use delimiters.

triple quotes: """

triple backticks: ```

triple dashes: ---

Angle brackets: < >

XML tags: <tag> </tag>

2. Tactic 2: Ask for structured output

Tactic 3: check whether conditions are satisfied

whether there're prompts?

Tactic 4. Few-shot prompting

Principle 2: Given the model time to think.

Tactic 1: specify the steps to complete the task

Tactic 2.: Instruct the model to work out its own solution before rushing to a conclusion

otherwise the model might neglect mistakes in the process

Reducing hallucinations:

First find relevant information, then

Answer the question based on evidence.

Prompt engineering is an iterative process

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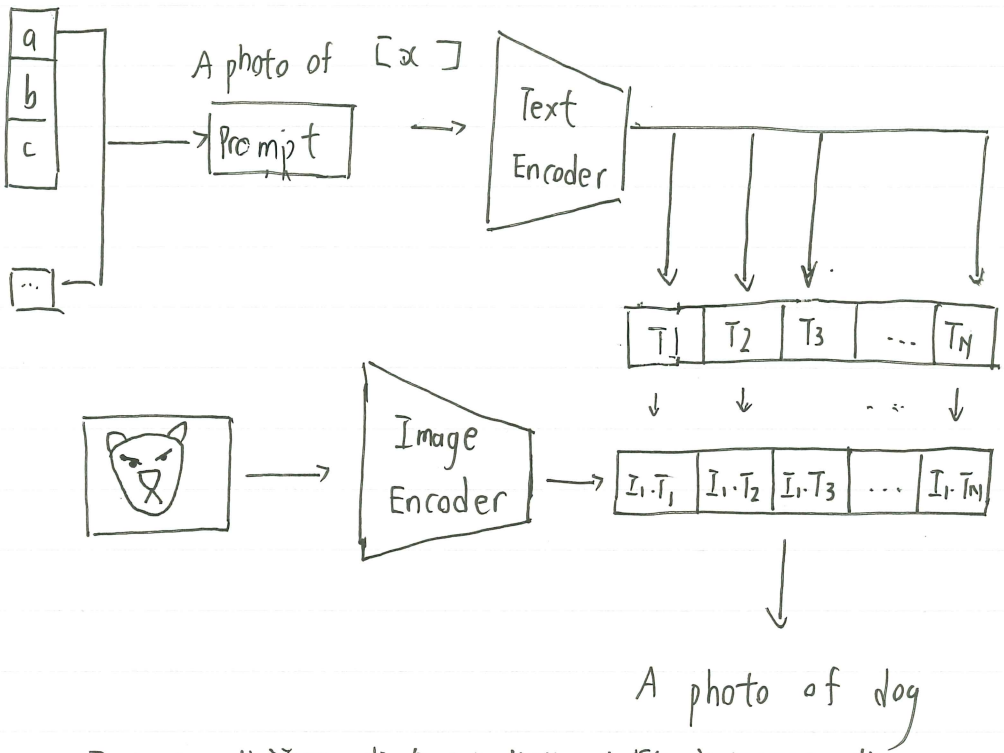
CLIP



- 通过对比式学习，省略生成式学习中繁琐实例细节，在抽象语义级别特征空间区分数据，拥有更简单的优化，更好的泛化
- 自回归预测 / 掩码完形填空 ——> 自监督训练
  目标函数与下游任务无关，而想要得到泛化能力强的特征

方法不新，但数据规模和模型规模实无前例

Transformer 的 Deep contextual representation learning 赋上下文语义环境学习方式，带来自监督范式下取之不尽用之不竭的文本监督信号

0.4 billion 数据（训练样本）

CV 与 NLP 的结合 使得能够学习多模态的特征，
很容易做 zero-shot 的迁移学习

把 训练任务变成对比任务 —> 效率 x4
（学习）

- Prompt engineering 的意义：
  ① 多义性
  ② 预训练时基本都是句子，只输入单词，抽取出的特征可能不好
- CLIP 唯一的数据增强就是随机裁剪
- Linear Probe：冻住主体参数，抽特征，只微调分类头
- 过于难的任务还得 few-shot
- 推文/视频下的 hashtag 可以作为监督信号的来源
- Clip 把原超参 temperature 优化为了可以学习的标量

伪代码：

```
# image_encoder      ResNet / Vision Transformer
# text_encoder       CBOW / Text Transformer
I[n, h, w, c]        minibatch of aligned images   (224 224 3)
T[n, l]              minibatch of aligned texts
W_i[d_i, d_e]        learned proj of image to embed
W_t[d_t, d_e]        learned proj of text to embed
t                    learned temperature
```

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```
# extract feature representations of each modality
I_f = image_encoder(I)
T_f = text_encoder(T)

# joint multimodal embedding   投影(单模态 -> 多模态)
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

# scaled pairwise cosine similarities [n, n]
logits = np.dot(I_e, T_e.T) * np.exp(t)

# symmetric loss function
labels = np.arrange(n)   正样本位于对角线,与MOCO只在0号(第一位)正样本不同
                         ground truth
loss_i = cross_entropy_loss(logits, labels, axis=0)
loss_t = cross_entropy_loss(logits, label, axis)
loss = (loss_i + loss_t)/2
```

局限性

- 想要达到专业领域SOTA水平,还需扩大1000倍 (Res 50只是基线)
- 细分类(如数个数,异常分类)情况下性能不好
- 泛化性在不属于0.4 billion的样本中很差,如MNIST
- 还得先给分类,CLIP再判断 (对比式和生成式的目标函数能否融合?)

self-supervision / self-training 或许能提高数据利用率

自监督　　伪标签

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、训练时重复使用已有监督训练数据集，可能有偏见

· 有时 one/ few shot 反而不如 zero-shot 好
  复杂概念无法用语言描述

意义：

· 打破了固定标签种类的范式，只需搜集图片-文本的配对
  用无监督的方式预测其相似性 / 生成
  方便做推理、zero-shot

新意度：100

有效性：100

问题大小：100 （灵活，多领域，高效）

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Convolutional Neural Networks

Edge detection.

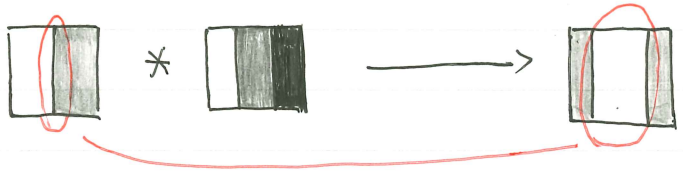
Vertical :

1	0	-1
1	0	-1
1	0	-1

Horizontal:

1	1	1
0	0	0
-1	-1	-1

filter kernel



1	0	-1
2	0	-2
1	0	-1

Sobel filter

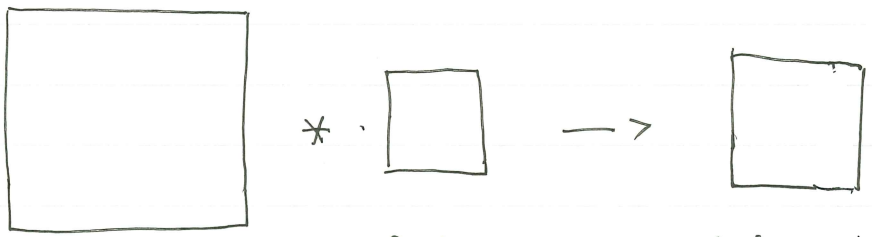
3	0	-3
10	0	-10
3	0	-3

Scharr filter

w_1	w_2	...
.	.	.
.	.	.

learnable ?

with backpropogation



$n \times n$

$f \times f$

$n-f+1 \cdot n-f+1$

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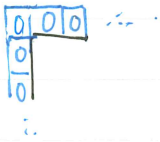
Padding



$n-f+1 \longrightarrow n+2p-f+1$

Valid convolution : no padding $n-f+1$

Same convolution: (padding) Soutput = Sinput $n+2p-f+1=n \Rightarrow p=\frac{f-1}{2}$

By convention, f is always odd $\longrightarrow$ To align with "central pixel"

Strided convolution

output: $\frac{n+2p-f}{s}+1 \cdot \frac{n+2p-f}{s}+1$

convolution in math textbook

Convolution in DL is Cross-correlation in Math

For convolution layer l

$f^{[l]}$ = filter size

$p^{[l]}$ = padding

$s^{[l]}$ = stride

Input: $n_H^{[l-1]} \times n_w^{[l-1]} \times n_c^{[l-1]}$

Output: $n_H^{[l]} \times n_w^{[l]} \times n_c^{[l]}$

$$n_{H/W}^{[l]} = \frac{n^{[l-1]} + 2p^{[l]} - f^{[l]}}{s^{[l]}} + 1$$

$n_c^{[l]}$ = number of filters

Each filter: $f^{[l]} \cdot f^{[l]} \cdot n_c^{[l-1]}$

Activation: $a^{[l]} \rightarrow n_H^{[l]} \times n_w^{[l]} \times n_c^{[l]}$

Weights: $f^{[l]} \cdot f^{[l]} \times n_c^{[l-1]} \times n_c^{[l]}$

bias: $n_c^{[l]} - (1,1,1,n_c^{[l]})$

Type of layers

1. Conv
2. Pool
3. FC

No.

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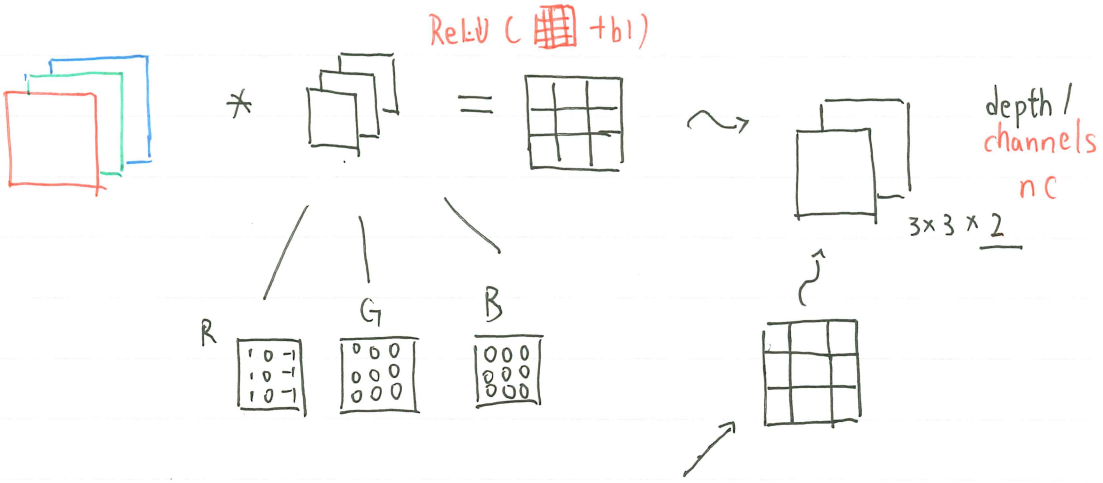
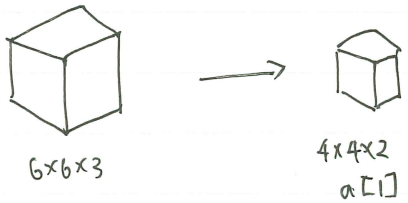
Convolution on volumn.



- We can have multiple filters focusing on different features.



N parameters remain same no matter how big input image is
— less likely to overfit

Max Pooling
Hyper Para: f s nothing to learn
2 2

Average pooling (less likely to use?
Used when very deep

No.

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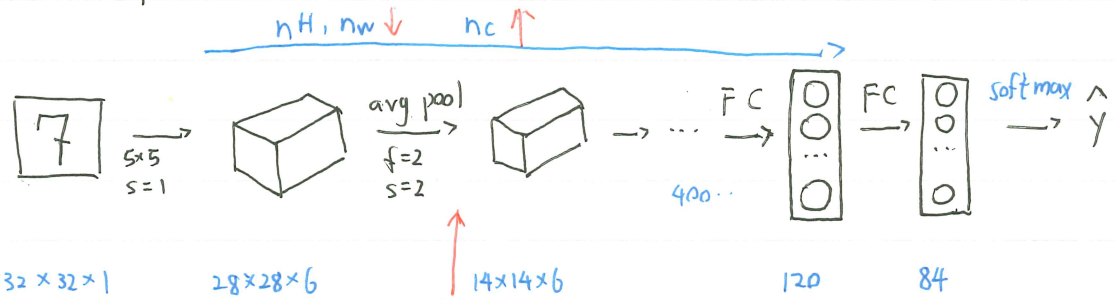
Le Net - 5

60k parameters.

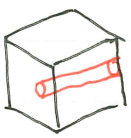


Used to have a non-linear (sigmoid / tanh.

Conv pool .... fc fc output

Alex Net. max pool

- Similar to LeNet, but much bigger
- ReLU (solve gradient diffusion of sigmoid in deeper nets)
- Multiple GPUs
- Local Response Normalization



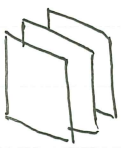
Normalization

- Utilize Dropout

VGG - 16 (Simpler, less hp)

138 M parameters

CONV = 3×3 filter, s = 1. same, MAX POOL = 2×2, s = 2



[CONV 64] → POOL → CONV 128 ×2, 256 ×2, 512 ×3 → POOL → FC 4096 → FC 4096 → Softmax 1000

512 big enough

Every step, as we go deeper

nw, nh /= 2

nc *= 2

very systematic uniform structure.

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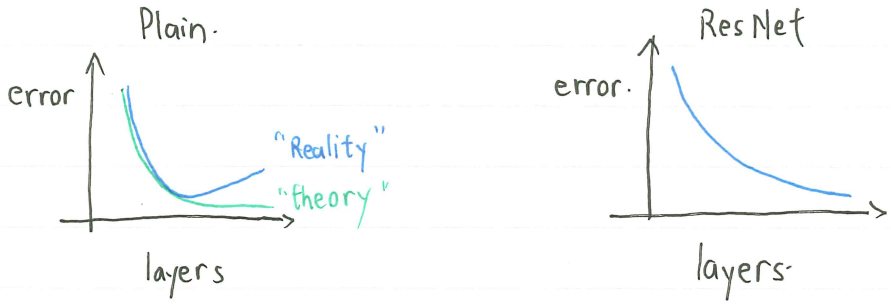
Res Net Residual block.

short cut / skip connection

$a^{[i]}$ → linear → ReLU → $a^{[i+1]}$ → linear → ReLU → $a^{[i+2]}$

main path.



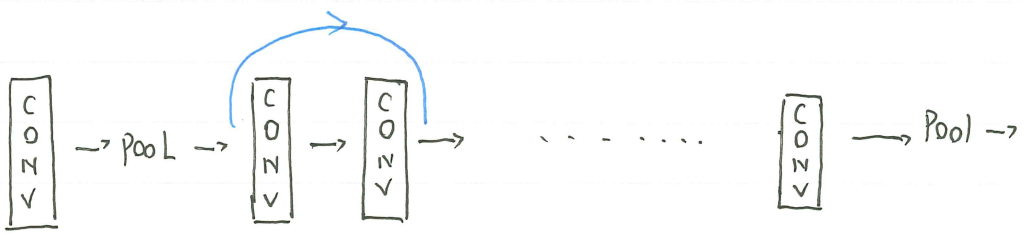
Allow for training deeper neural networks

Why Residual Network works

Normally $a^{[i]} = a^{[i+2]}$, it won't affect overall performance

More chances to choose correct parameter to improve.

* if dimensions of $a^{[i]}$ and $a^{[i+2]}$ are different, add a weight matrix



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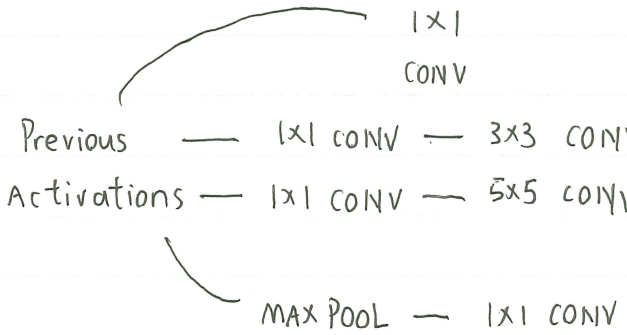
Inception block



- To prevent overfitting, we also add some softmax branches
  (like a regularizing effect)

Depthwise Convolution

$6\times6\times3 \quad * \quad 3\times3\times n_c \longrightarrow 4\times4\times3$

Cost = filter params × filter positions × # of filters

Pointwise Convolution

$4\times4\times3 \quad * \quad 1\times1\times n_c \longrightarrow 4\times4\times n_c'$

Cost is similiar to above.

Depthwise Separable Convolution

Depthwise Pointwise.

most computational efficient compared with normal convolution

$\frac{1}{n_c'} + \frac{1}{f^2}$ more efficient

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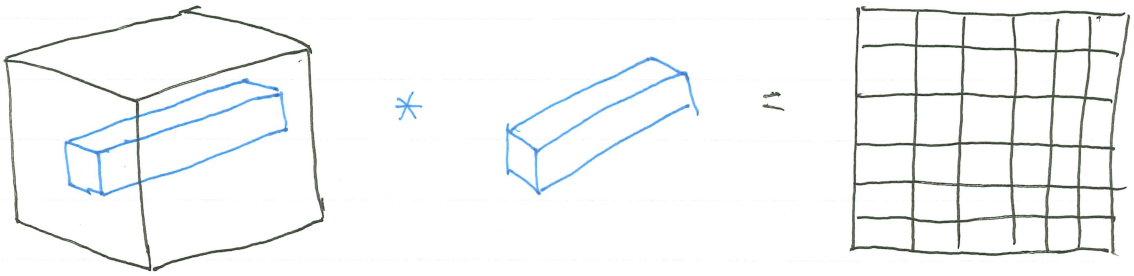
1×1 convolution: (network in network)

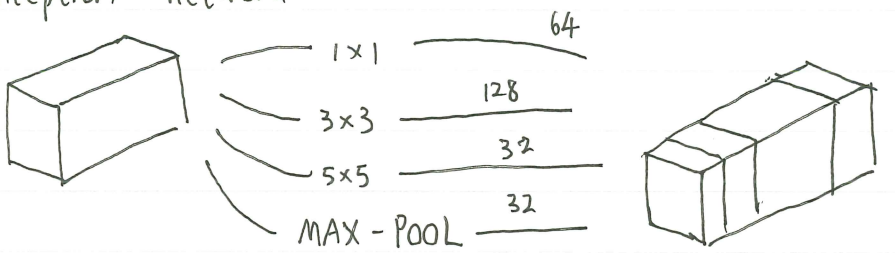


6×6×32 1×1×32 6×6×#filters

similiar to a FC layer that applies to each positions

Adjust the channel. (升/降维特征矩阵)

Inception network.

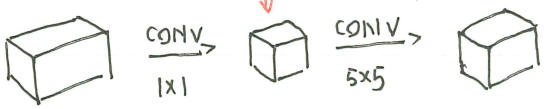


n·n·192 n·n·256

No need to pick kernel size, let it learn

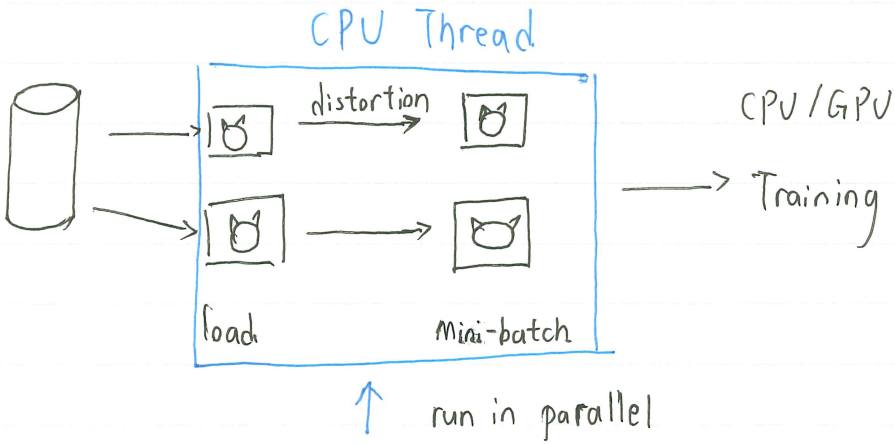
Problem: computational cost

"bottleneck layer"



Computation 120 m → 12.4 m

If bottleneck layer is implemented properly, you can shrink down representation size significantly while doesn't seem to hurt performance



Two sources of knowledge

- Labeled data
- Hand engineered features / network architecture

Tip. —— Ensembling

- Train several networks independently and average their outputs

Multi-crop at test time.

- Run classifier on multiple versions of test images and average

Reduce speed · better not use it when building products results

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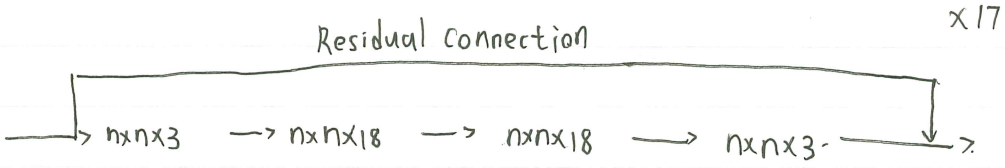
Mobile Net V2 Bottle Neck



Expansion Depthwise Pointwise.

(Projection due to memory limit)

allow for learning richer and more complex functions

Efficient Net: How to choose. r (resolution), d (depth) and w (width)?

Transfer Learning

* Freeze previous parameters. modify the last layer
* Use others' parameters as initialization.
  . More data —> less frozen layers

Data Augmentation.

- Mirroring
- Random Cropping
- Rotation
- Shearing
- Local Warping 局部约束
- Color shifting

PCA color augmentation: : more changes on R·B · less on G

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