# RS&NLP选修 Lesson-02

# 前情提要

- 根据业务场景不同，推荐系统可以演化得差异很大。因此，要注意学习算法背后的思想，做到融会贯通

- 实例：视频相关推荐。拆解和抽象为机器学习问题，进而用SGNS的方式去解决

- NLP和RS是算法的两个重要应用方向，其背后的思想可以找到很多相通和借鉴之处

- 理论提升：和矩阵分解的等价性

# 回顾：视频相关推荐

- 分为3个步骤：
  - Step1 构建序列：预处理用户的行为日志，使之适配算法
  - Step2 求解相似性：利用skip-gram with negative sampling计算item之间的相似性
  - Step3 Faiss建立索引：利用索引库为item建立索引，供线上推荐使用

# Step1 构建序列

- Input：曝光/点击日志
- Output：点击序列
- Code：实操

# Step2 求解相似性

- Input：点击序列
- Output：item -> vector
- Code：实操

# Step3-1 建立索引

- Input：item -> vector
- Output：索引文件
- Code：实操

# Step3-2 用索引查找

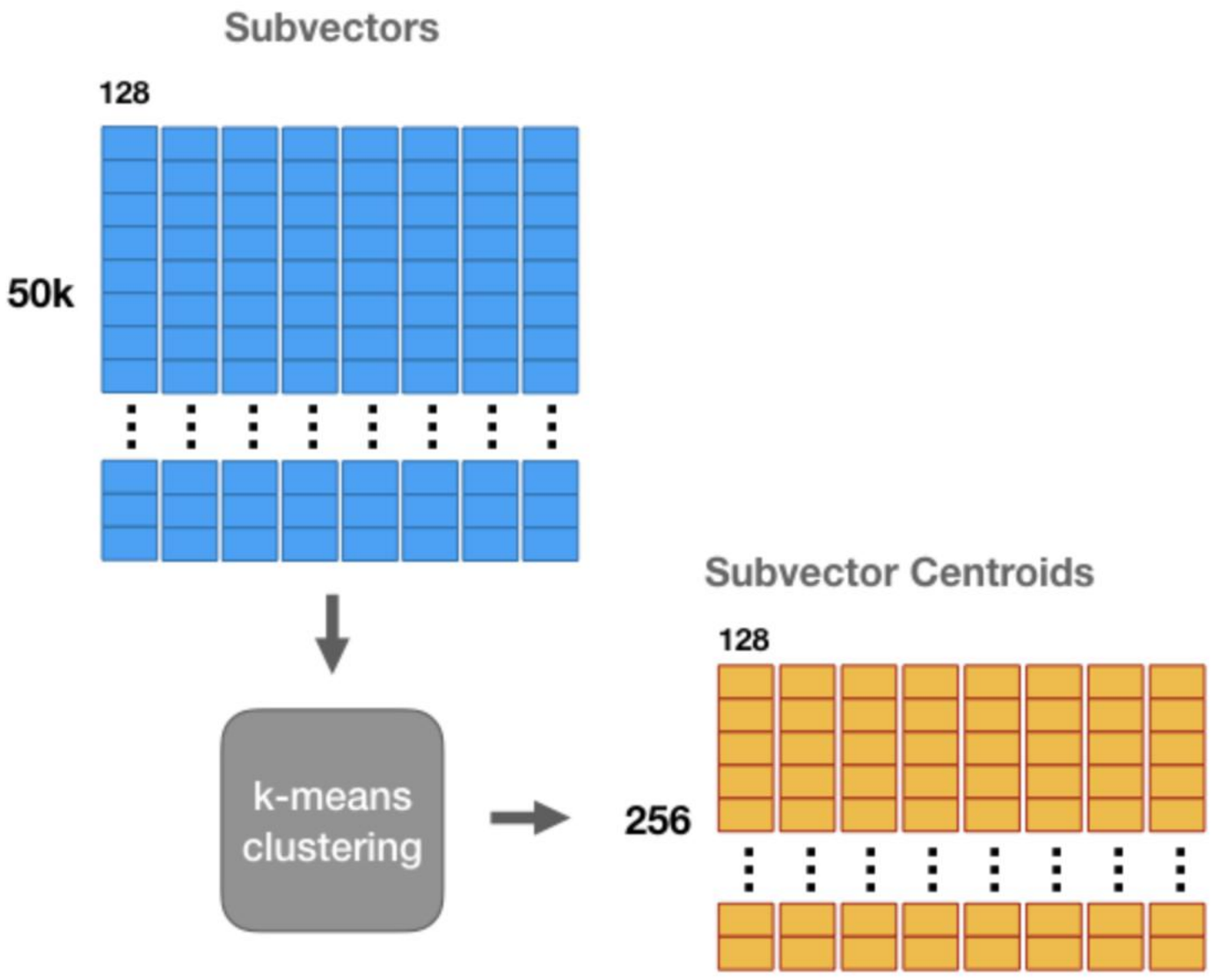
- Input：索引文件，key
- Output：key的最近邻
- Code：实操

# Index factory

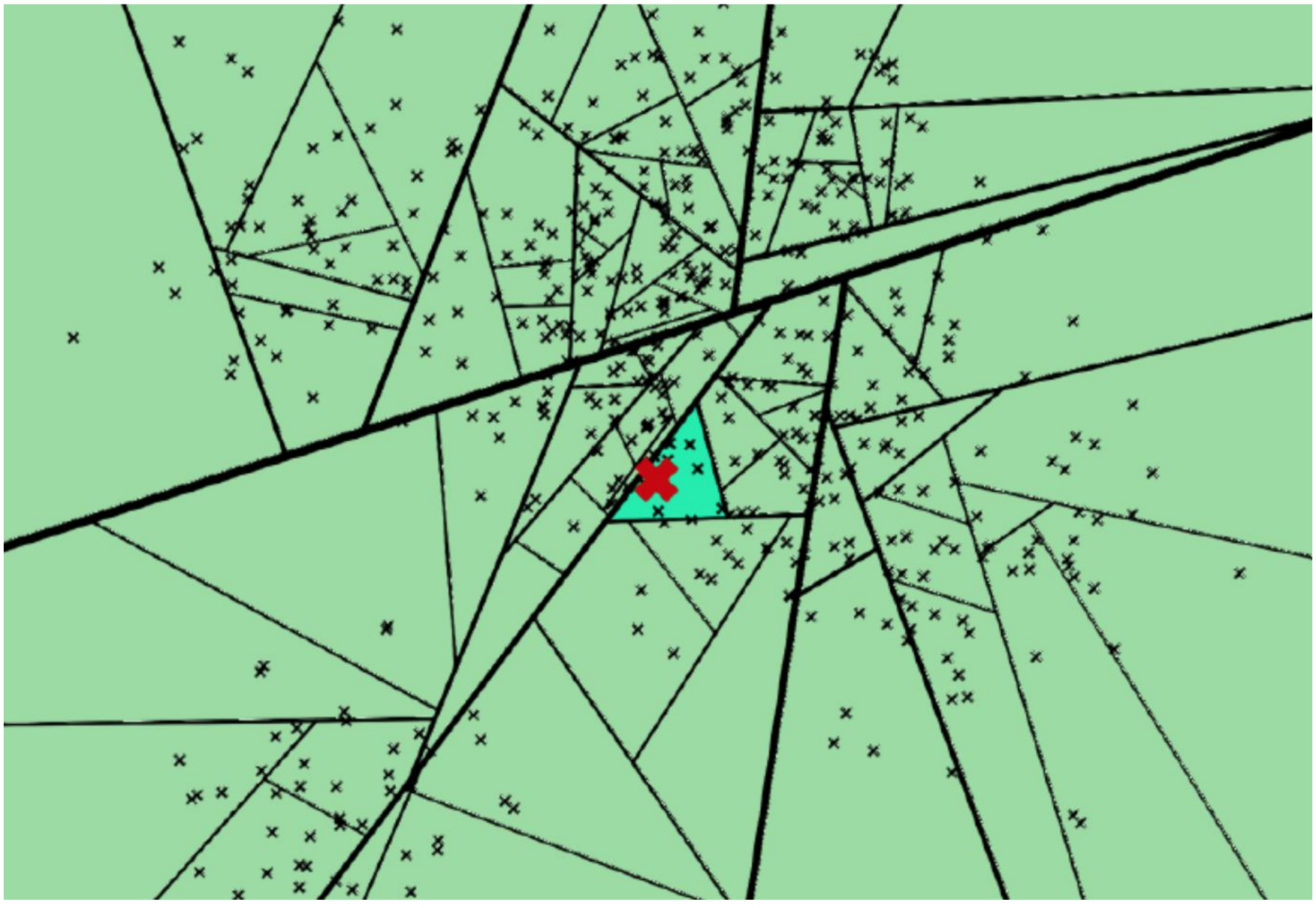
| Method | Class name | index_factory | Main parameters | Bytes/vector | Exhaustive | Comments |
|---|---|---|---|---|---|---|
| **Exact Search for L2** | IndexFlatL2 | Flat | d | 4*d | yes | brute-force |
| **Exact Search for Inner Product** | IndexFlatIP | Flat | d | 4*d | yes | also for cosine (normalize vectors beforehand) |
| **Hierarchical Navigable Small World graph exploration** | IndexHNSWFlat | 'HNSWx,Flat` | d, M | 4*d + 8 * M | no | |
| **Inverted file with exact post-verification** | IndexIVFFlat | IVFx,Flat | quantizer, d, nlists, metric | 4*d | no | Take another index to assign vectors to inverted lists |
| **Locality-Sensitive Hashing (binary flat index)** | IndexLSH | - | d, nbits | nbits/8 | yes | optimized by using random rotation instead of random projections |
| **Scalar quantizer (SQ) in flat mode** | IndexScalarQuantizer | SQ8 | d | d | yes | 4 bit per component is also implemented, but the impact on accuracy may be inacceptable |
| **Product quantizer (PQ) in flat mode** | IndexPQ | PQx | d, M, nbits | M (if nbits=8) | yes | |
| **IVF and scalar quantizer** | IndexIVFScalarQuantizer | IVFx,SQ4 "IVFx,SQ8" | quantizer, d, nlists, qtype | SQfp16: 2 * d, SQ8: d or SQ4: d/2 | no | there are 2 encodings: 4 bit per dimension and 8 bit per dimension |
| **IVFADC (coarse quantizer+PQ on residuals)** | IndexIVFPQ | IVFx,PQy | quantizer, d, nlists, M, nbits | M+4 or M+8 | no | the memory cost depends on the data type used to represent ids (int or long), currently supports only nbits <= 8 |
| **IVFADC+R (same as IVFADC with re-ranking based on codes)** | IndexIVFPQR | IVFx,PQy+z | quantizer, d, nlists, M, nbits, M_refine, nbits_refine | M+M_refine+4 or M+M_refine+8 | no | |

根据需求去选择
具体算法

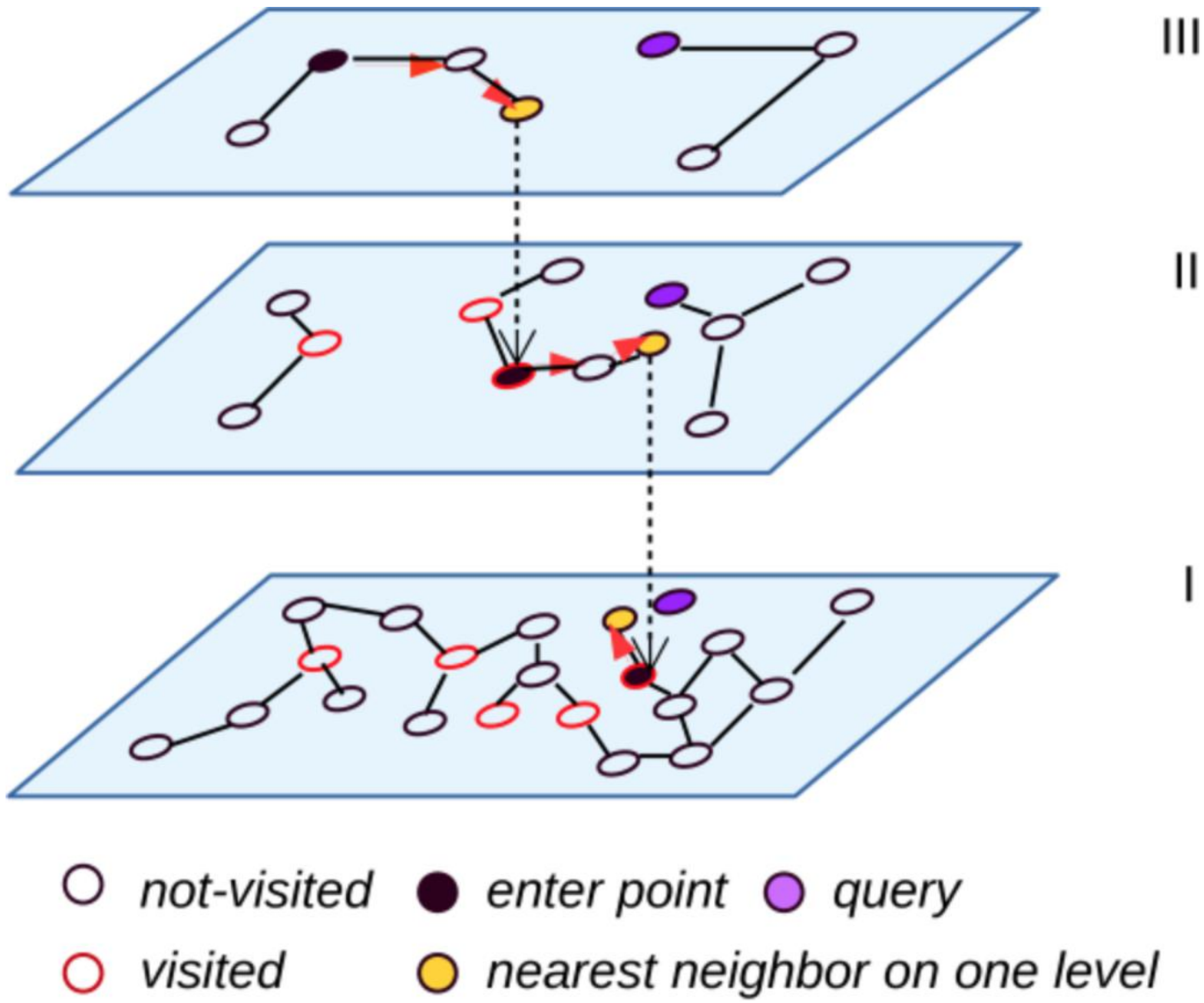
# PQ算法


Subvectors
128
50k
k-means
clustering
Subvector Centroids
128
256

# Annoy算法



# HNSW算法


III
II
I
not-visited
enter point
query
visited
nearest neighbor on one level

# 选择索引算法时的一些指导原则

- 有多少向量需要建索引
- 索引database更新的频率需要如何
- 召回率是否满足需求
- 索引算法所支持的距离度量是否适配

“有没有更好的方式？”

# 基于SGNS做召回的局限性

- 无监督方式，不是直接优化目标
- 没法结合side information

# 深度语义匹配模型DSSM

- 主要贡献
  - 利用点击数据（有监督）
  - 利用深度学习（学习能力强）
  - Word hashing（解决大词表问题）


# 纸上得来终觉浅，绝知此事要躬行

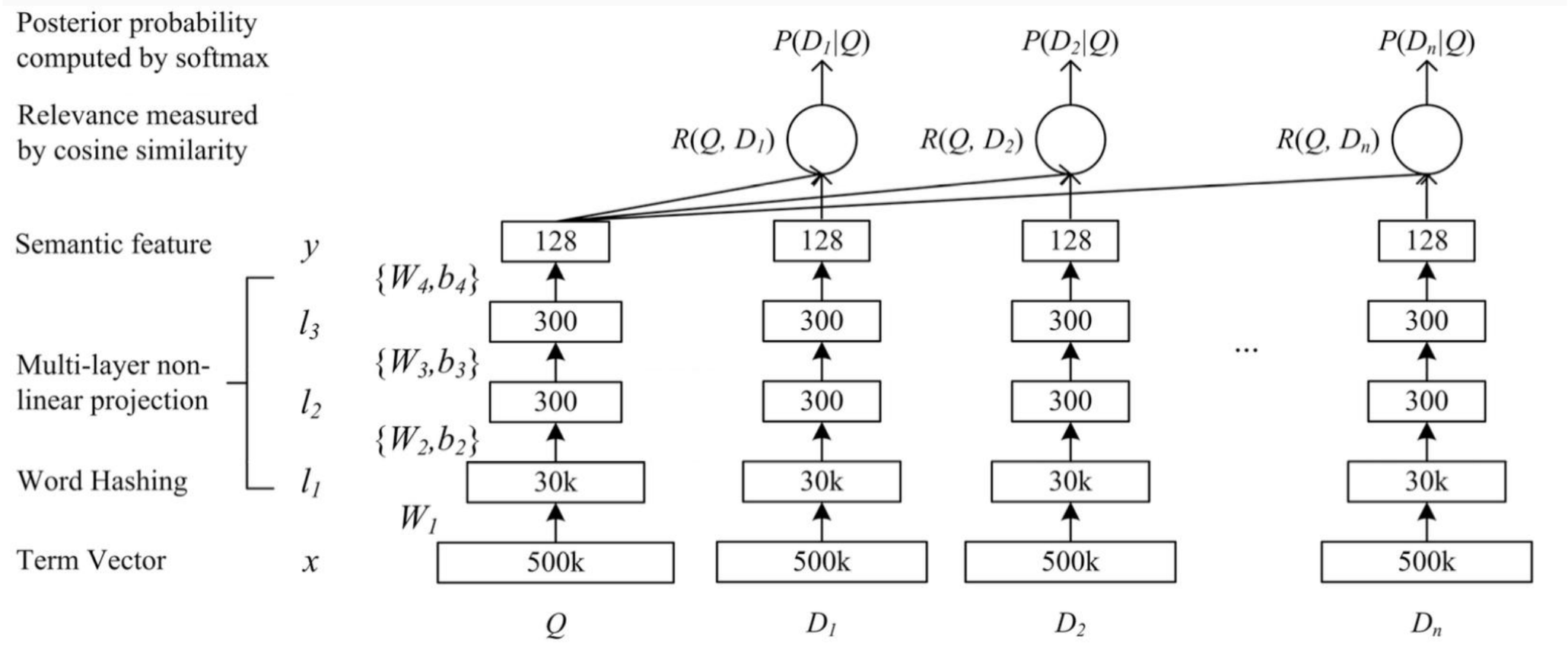
# TensorFlow还用介绍吗

**TensorFlow 是一个端到端开源机器学习平台**

# 用TF实现DSSM都需要做什么

- 设计和定义模型结构
- 构造训练数据
- 使用GPU进行训练
- 导出训练好的模型
- 导出embedding向量

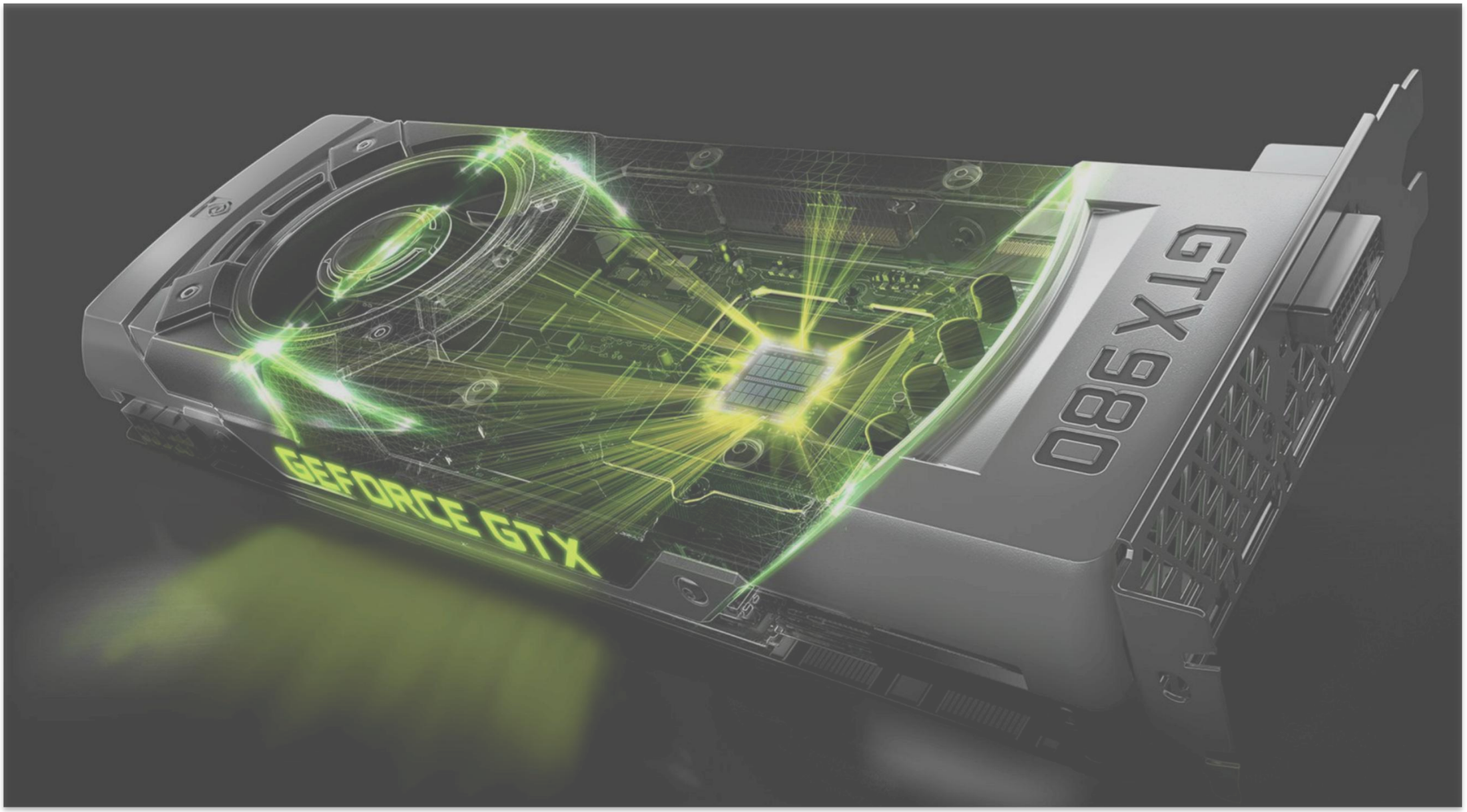
# 设计和定义网络结构


Posterior probability computed by softmax
Relevance measured by cosine similarity
Semantic feature
Multi-layer non-linear projection
Word Hashing
Term Vector
y
$l_3$
$l_2$
$l_1$
x
$\{W_4,b_4\}$
$\{W_3,b_3\}$
$\{W_2,b_2\}$
$W_1$
$P(D_1|Q)$
$P(D_2|Q)$
$P(D_n|Q)$
$R(Q, D_1)$
$R(Q, D_2)$
$R(Q, D_n)$
128
300
30k
500k
...
Q
$D_1$
$D_2$
$D_n$

# 构造训练数据

- 数据下载
- 格式介绍
- 处理成什么样

# 一些必要的辅助函数（代码）




# 如何使用GPU（代码）

# 导出模型和向量（代码）

“关于模型的讨论。”

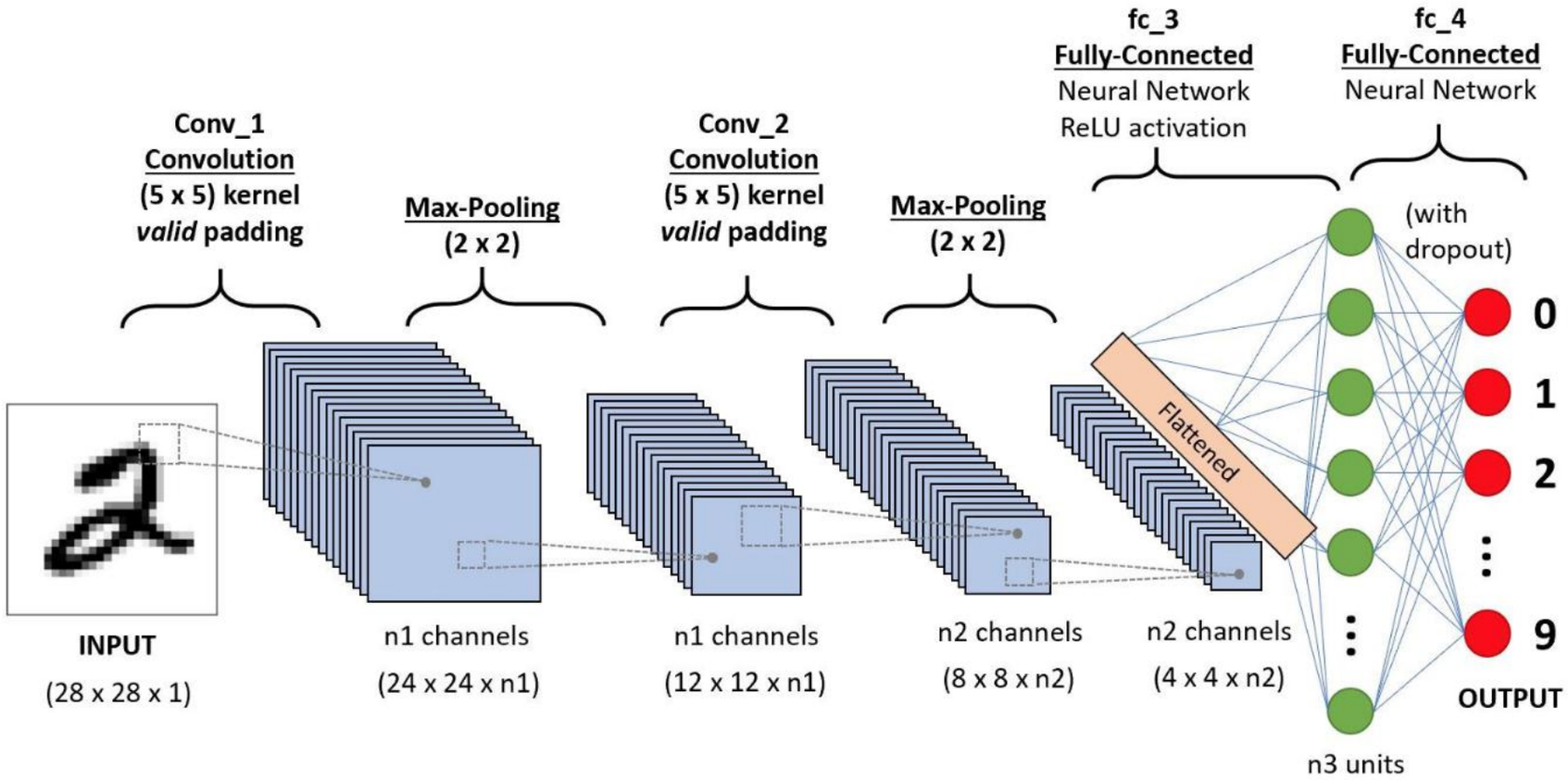
# 基于DNN的模型有什么缺点

- 同等看待用户的行为，而没有考虑到上下文
- 无法充分反映用户的兴趣

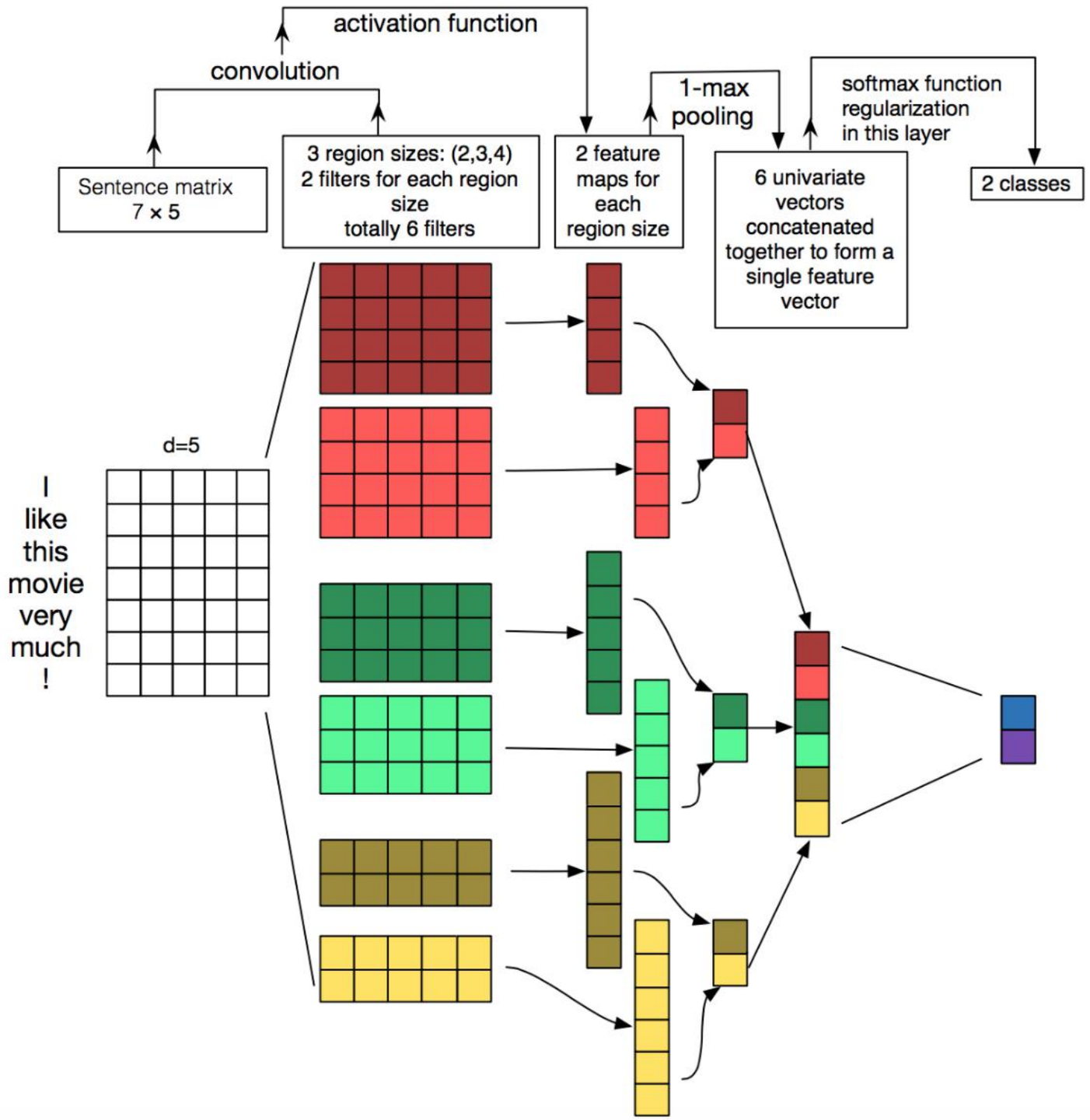
# 什么叫卷积

$$(f*g)(n)=\sum_{\tau=-\infty}^{\infty}f(\tau)g(n-\tau)$$

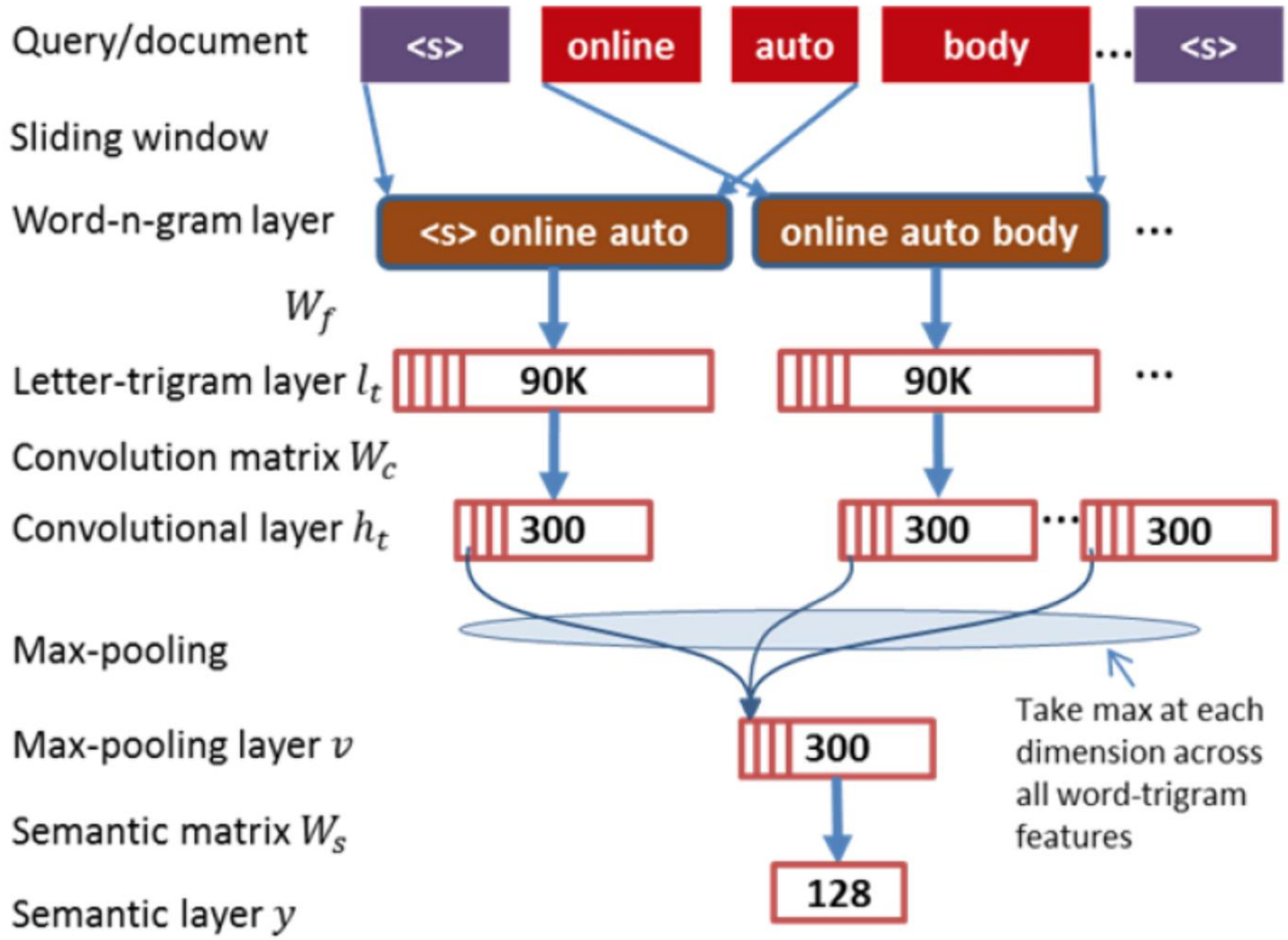
# CNN用于图像


Conv_1
Convolution
(5 x 5) kernel
valid padding
Max-Pooling
(2 x 2)
Conv_2
Convolution
(5 x 5) kernel
valid padding
Max-Pooling
(2 x 2)
fc_3
Fully-Connected
Neural Network
ReLU activation
fc_4
Fully-Connected
Neural Network
(with
dropout)
Flattened
INPUT
(28 x 28 x 1)
n1 channels
(24 x 24 x n1)
n1 channels
(12 x 12 x n1)
n2 channels
(8 x 8 x n2)
n2 channels
(4 x 4 x n2)
n3 units
0
1
2
9
OUTPUT

# CNN用于NLP


activation function
convolution
1-max pooling
softmax function regularization in this layer
Sentence matrix 7 × 5
3 region sizes: (2,3,4) 2 filters for each region size totally 6 filters
2 feature maps for each region size
6 univariate vectors concatenated together to form a single feature vector
2 classes
d=5
I
like
this
movie
very
much
!

# CNN改进后的结构


Query/document
<s>
online
auto
body
...
<s>
Sliding window
Word-n-gram layer
<s> online auto
online auto body
...
$W_f$
Letter-trigram layer $l_t$
90K
90K
...
Convolution matrix $W_c$
Convolutional layer $h_t$
300
300
...
300
Max-pooling
Max-pooling layer $v$
300
Take max at each dimension across all word-trigram features
Semantic matrix $W_s$
Semantic layer $y$
128

“在TF里修改模型结构。”

# 下一步做什么

- 模型serving
- 确保线上线下数据分布的一致性
- badcase分析
- 调整方案

# 思考

- 为何深度学习有效
- 如何对行为的时序建模
- 不用深度学习怎么做

# 总结&回顾

- 承接上回：高维空间向量搜索算法（PQ/Annoy/HNSW）
- SGNS框架的局限性
- 用TF实现一个DSSM模型
- 如何利用CNN结构进行改进
- 理论提升