Quora Question Pairs Competition

YesofCourse Team Solution

Pang Liang, Fan Yixing, Hou Jianpeng,

Yue Xinyu, Niu Guocheng

中国科学院网络数据科学与技术重点实验室
Key Laboratory of Network Data Science & Technology, CAS

Content

- Introduction
- Solution
  - Pre-processing
  - Feature-Engineering
  - Deep Model
  - Traditional Model
  - Stacking
  - Post-processing
- Conclusion

Team Introduction

Niu Guocheng

Master

@Baidu

Researches: Natural Language Processing and Machine Learning

Pang Liang

PhD. candidate

@ICT

Researches: Information Retrieval, Matching Learning, Deep learning

Hou Jianpeng

Master

@Google

Researches: Machine Learning and Distributed Computing

Fan Yixing

PhD. candidate

@ICT

Researches: Information Retrieval, Matching Learning, Deep learning

Yue Xinyu

Master

@ICT

Researches:Recommendation, Data Mining, Machine Learning

Team Introduction

$\mathbf{1}^{st}$ Place, Awarded in **2016 BYTECUP**

$\mathbf{1}^{st}$ Place, Awarded in **China Telecom Big Data Application Contest**

$\mathbf{1}^{st}$ Place, Awarded in **SIGHAN-2015 Chinese Spelling Check Task**

$\mathbf{1}^{st}$ Place, Awarded in **RecSys2013: Yelp Business Rating Prediction**

Task Problem

Quora

A place to share knowledge and better understand the world

“ Why is WeChat more popular than WhatsApp in China given that WhatsApp is more popular elsewhere? ”

“ WeChat is quite popular in China. Are there many people from other countries using WeChat to contact each other? ”

这是官方给出的结果精度评价标准？还是作者自己定义的？

Task Dataset

- Dataset Statistics

!!! Computer-generated pairs

	Question pairs	Distinct pairs	Total questions	Pos vs Neg
Training	404,290	404,258	537,373	**36.92%**
Testing	2,345,796	2,339,396	4,340,277	**16.5%**

- Dataset Statistics

id	quesition1	question2	Is_duplicate
0	How do I prevent breast cancer?	Is breast cancer preventable?	0
1	How does 3D printing work?	How do 3D printing work?	1

- Evaluation

$$logloss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{i,j}\log(p_{i,j})$$

Task Participants

Microsoft

airbnb

IBM

PEKING UNIVERSITY 1898

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

UCL

3307

TSINGHUA UNIVERSITY 1911

UNIVERSITY OF MASSACHUSETTS AMHERST 1863

Kaggle Rankings

1	Gilberto Titericz Junior
2	Stanislav Semenov
3	Μαριος Μιχαηλιδης KazAnova
4	Faron
5	idle_speculation
6	Eureka
7	Silogram
8	Little Boat
9	utility
10	raddar

Final Leaderboard

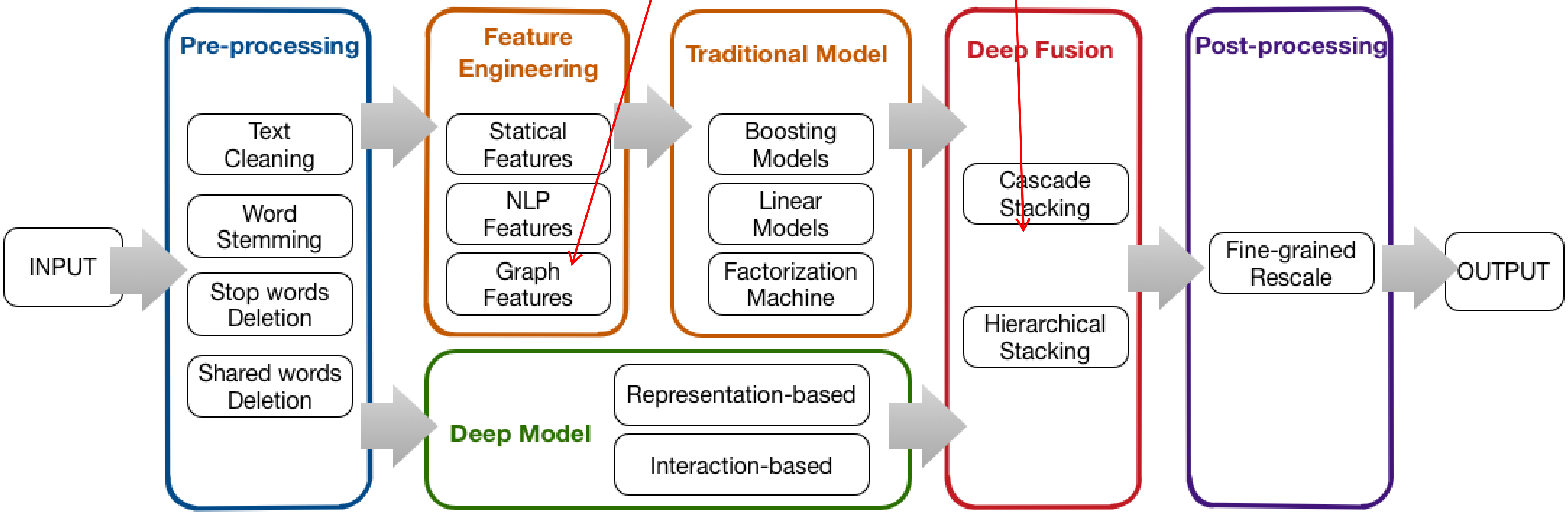
#	△pub	Team Name	Kernel	Team Members	Score	Entries
1	—	DL guys			0.11580	263
2	—	Depp Learning			0.11670	196
3	—	Jared Turkewitz & sjv			0.11756	178
4	—	YesOfCourse			0.11768	189
5	—	Qingchen | KazAnova | Faron			0.11851	219
6	—	LAMAA power			0.11887	406
7	▲ 2	aphex34			0.12072	166
8	—	NLPFakers		+3	0.12239	250
9	▼ 2	Unduplicated Duplicates		+4	0.12248	314
10	▲ 1	♬ ♪ b.a.s.s. ♩ ♬			0.12296	271

Architecture

关于“图论特征”，之前我没有想过

这里的stacking就是如何把之前做的那些特征都用起来，用的是boosting和stacking

The framework of our solution:



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Preprocessing

Made some different versions of original data:

- Lower case
- Text cleaning
- Stop words removal
- Word stemming
- Punctuation Cleaning
- Shared words deletion
- Part of Speech Group

Preprocessing • **Text Cleaning**

- Substitute Abbreviation
  - ' n‘t ' => ' not '
  - ' that’s ' => ' that is '
  - ' US ' => ' America '
- Substitute Special Character
  - ' \$ ' => ' dollar '
  - ' ₹ ' => ' rs '
- Substitute Numbers
  - ' one ' => ' 1‘
  - ' 6k' => ' 6000'

Preprocessing • **POS Group**

- Extract different part of speech from origin sentences.

Origin Sentences

How do I start learning machine learning?
How should I go about learning Machine Learning?

Noun Words

Machine learning
Machine learning

Verb Words

Start learning
go about learning

… …

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Feature Engineering

关于这个sentence level，再加上document level，注意看他们是怎么由词到句再到paragraph的

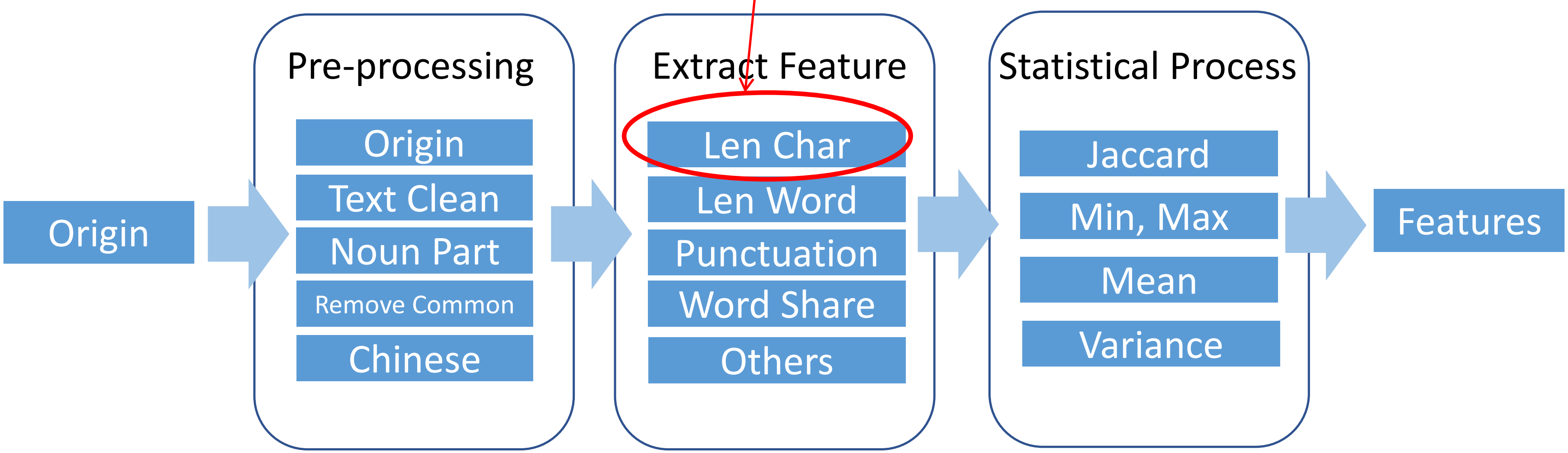
- Statistical
  - Powerful Words
  - Interrogative Words
  - FuzzyWuzzy
- NLP
  - Topic Model
  - Key Phrase Extraction
  - Dependency Parsing
  - Differential Analysis
  - Cross-Language Features
- Representation
  - Word Level
  - Sentence Level
- Graph
  - Nodes and Edges
  - Structure Information
  - Propagation Information

这里说的用到的自然语言的特征处理是关于topic modeling这些，我怎么感觉作者有点特意去用这个技术，为了学这个技术而且用这个技术

这个特征：单词的长度特征，我之前也没有想过

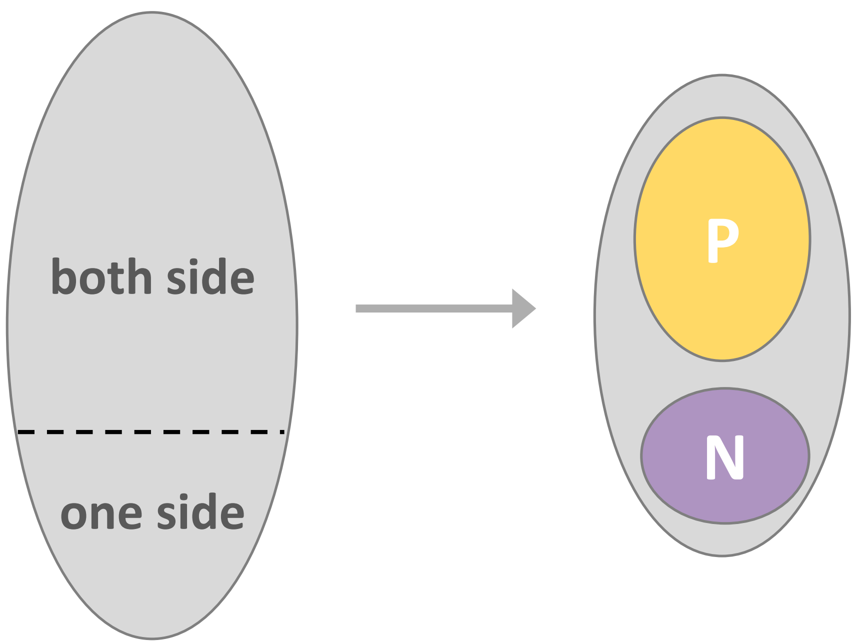
Statistical Features

- Len Char, Len Word, Len Vowel, Punctuation Num, Word Match Share et al
- Multi Channel including Origin, Text Cleaning
- Multi Process Method including Jaccard Ratio, Min, Max, Mean, Variance et al



Statistical Features • **Powerful Words**

- Words which make two sentences express same meaning.



data set
contained specified word

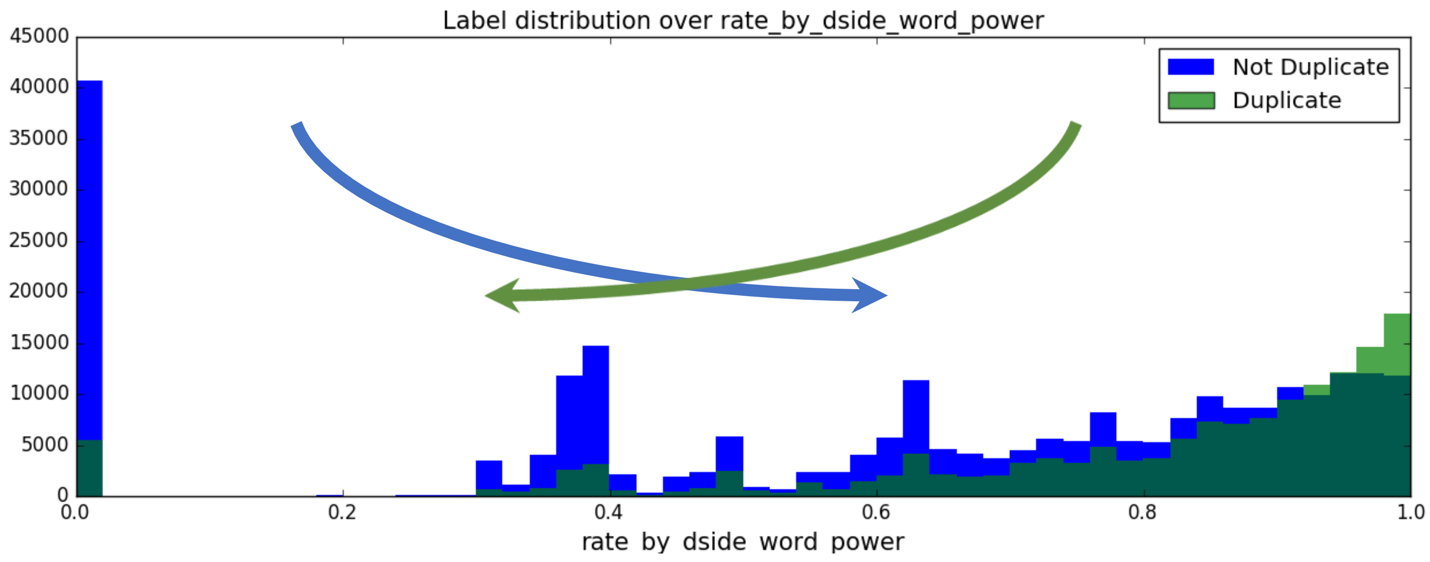
both side data set
contained specified word

$$p_i = \frac{size(P)}{size(P+N)}$$

$$p_{y=0} = \prod (1 - p_i)$$

Statistical Features • **Powerful Words**

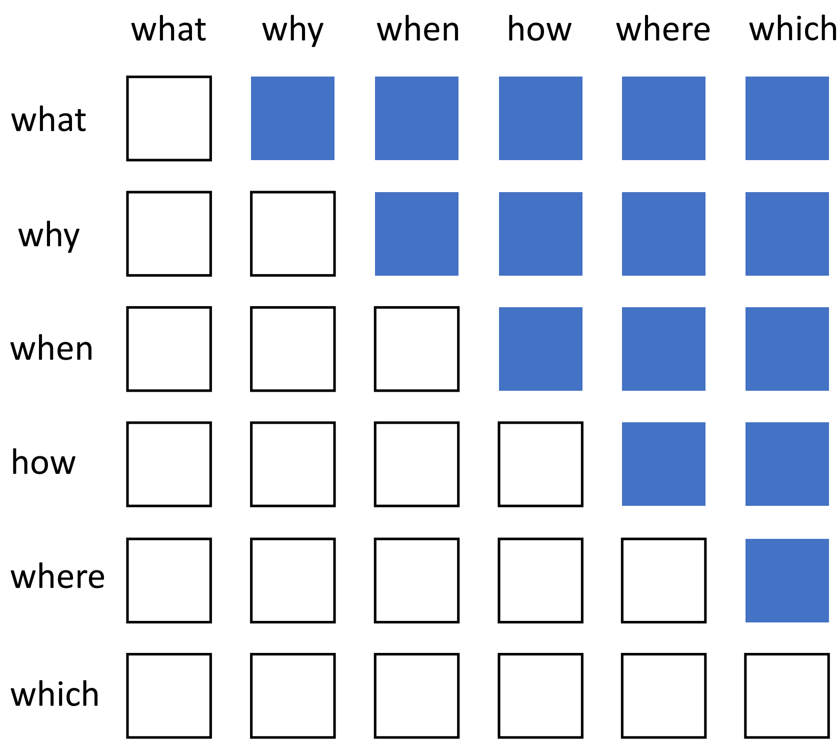
- Words which make two sentences express same meaning.



Statistical Features

- **Interrogative Words**

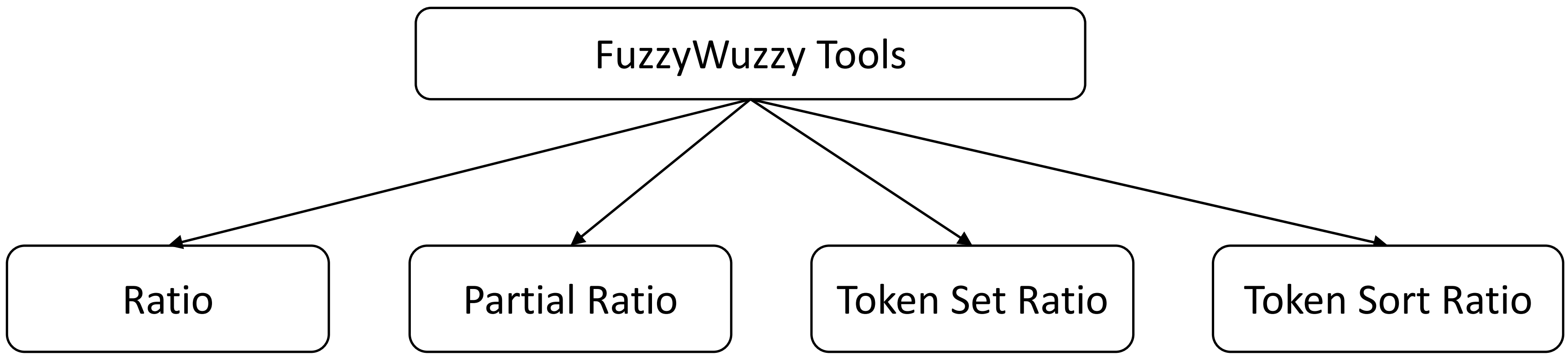
- Build a coexistence matrix for interrogative words.



这个“术语”我也没有听过

Statistical Features • **FuzzyWuzzy**

- Edit Distance calculation
- Multi types edit distance catch various info



Instance

How do I apply for internship in IT firms?
How do I apply for internships in IT companies?
Label: 1

FuzzyWuzzy Features

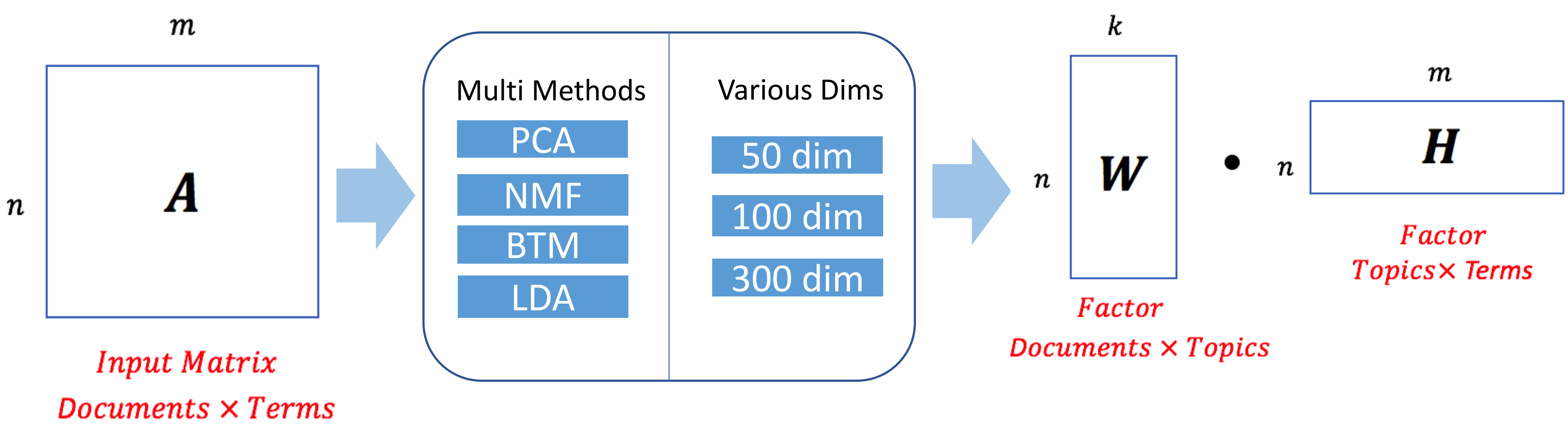
Ratio:88
Partial_ratio:88
Token_set_ratio:80
Token_sort_ratio:87

NLP Features

- Topic Model
  - PCA、NMF、BTM、LDA
- Key Phrase Extraction
  - SG Rank
- Dependency Parsing
  - Principal component extraction
  - Semantic tree
- Differential Analysis
  - Part-of-speech、Named-entity、Brown-cluster
- Cross-Language Features
  - Translate into Chinese

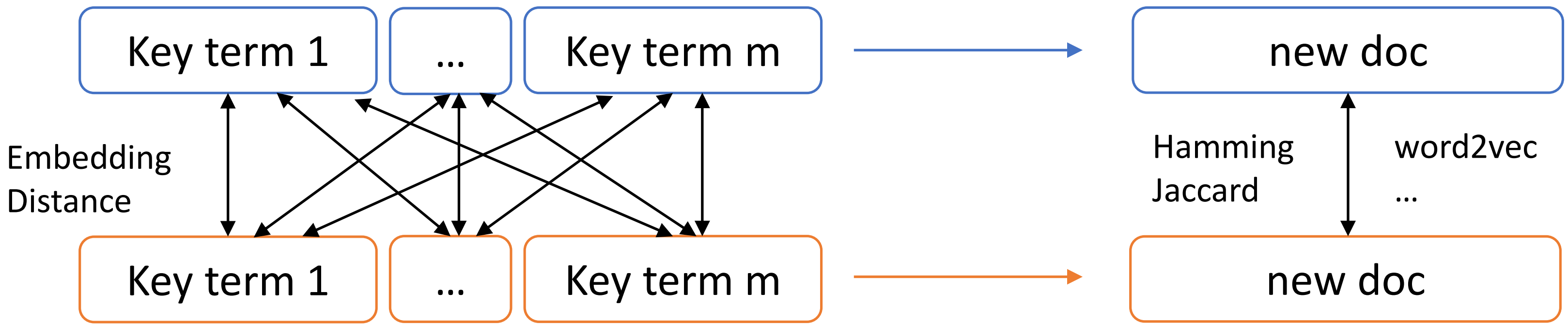
Topic Model Features

- Construct TF-IDF Matrix
- Matrix Factorization including PCA、NMF、BTM、LDA et al with several dimensions



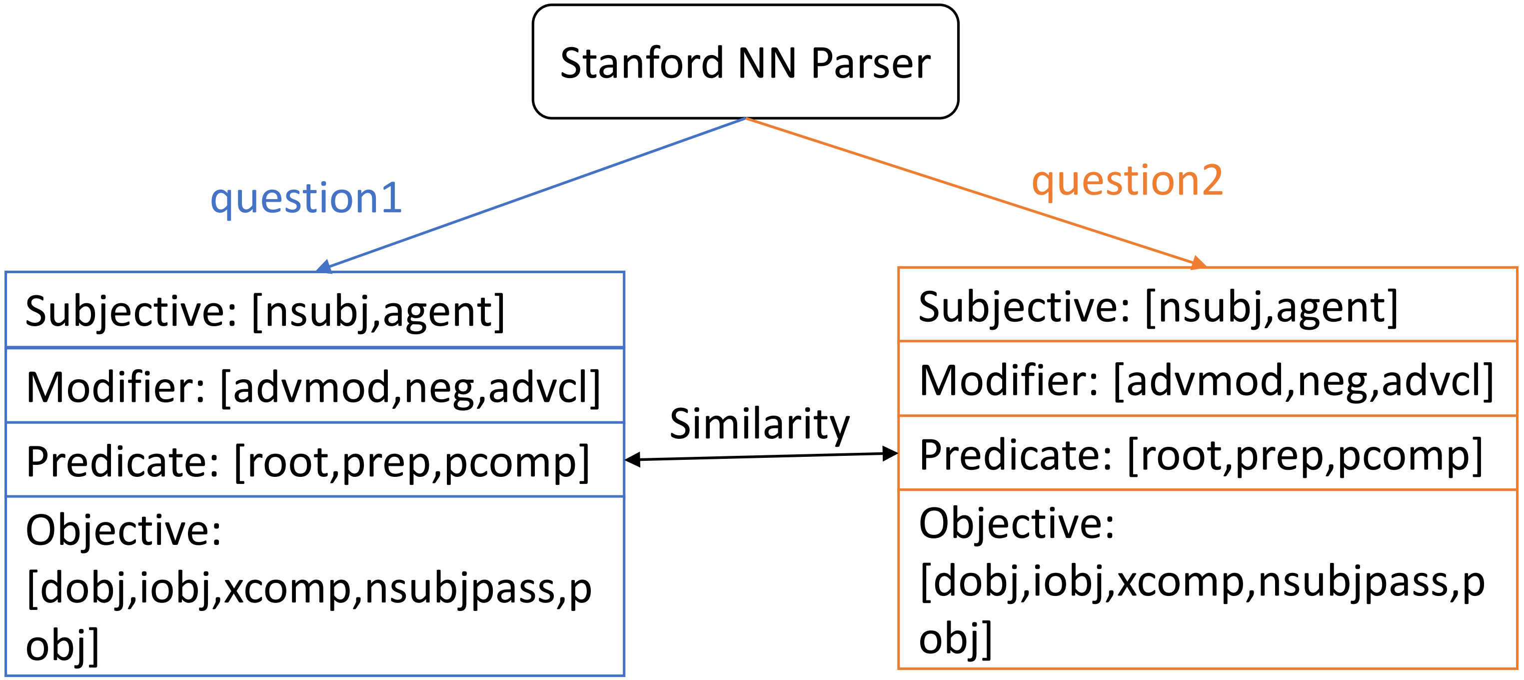
Key Phrase Extraction

- Unsupervised Key-phrase Extraction
- A hybrid statistical-graphical algorithm SGRank[Sem 2015]
- Reattach key terms as the new doc instead of origin one



Dependency Parsing

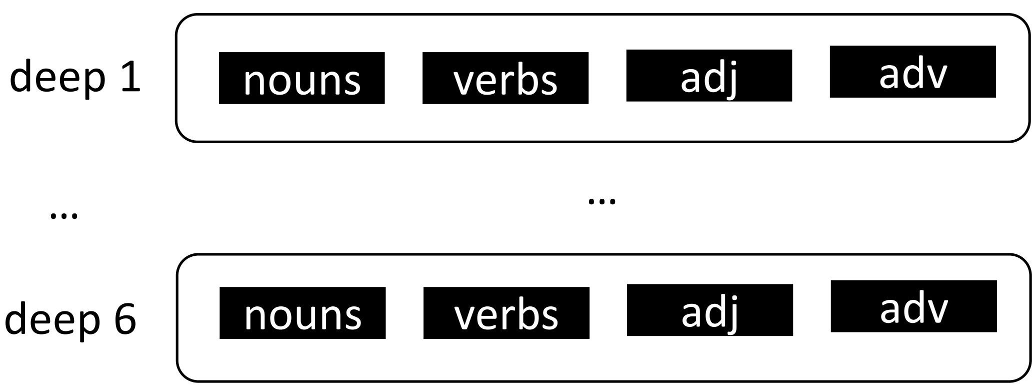
- Sentence principal component extraction
- Light rules can be summed up based on Dep-Parser

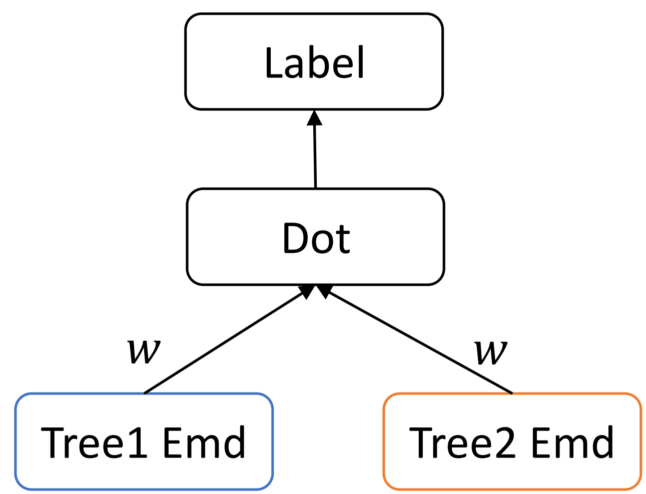


Dependency Parsing

- Semantic information can put to use on trees
- Weights of part-of-speech on different depth are different
- Weights can be supervised learned on training set

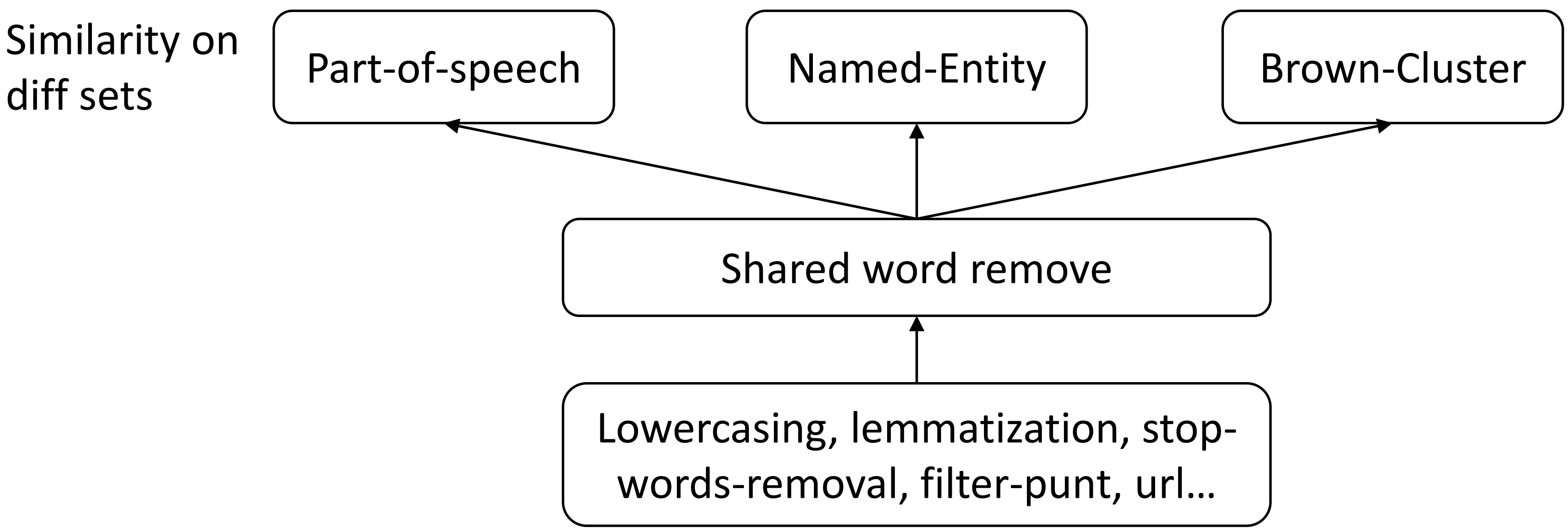
$$TreeEmd = \sum_{i=1}^{6} \sum_{j=1}^{4} PosEmd_{i,j} * w_{i,j}$$





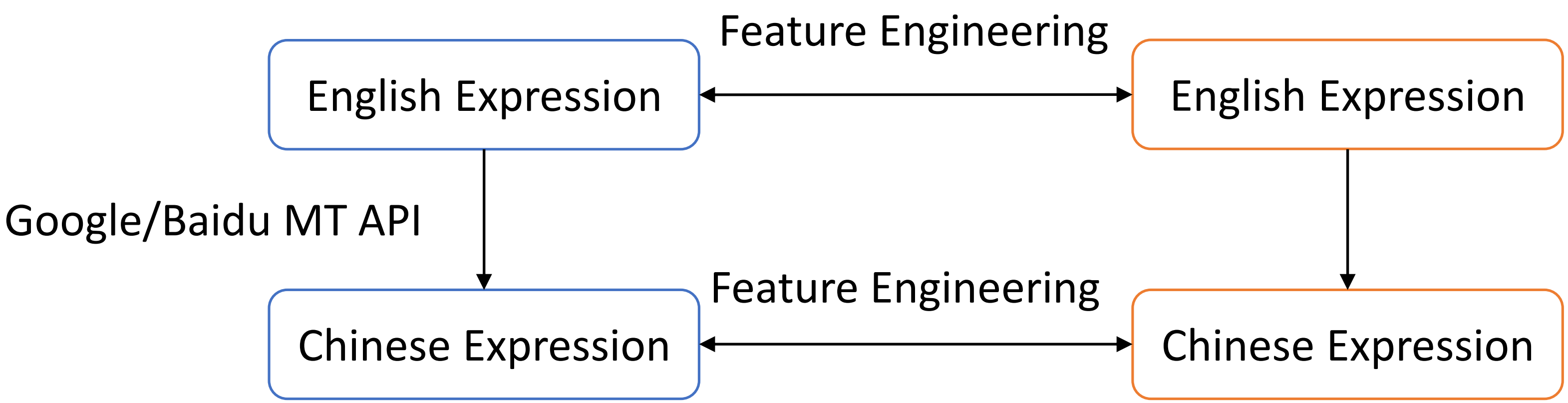
Differential Analysis

- Same words between pairs can confuse us in some ways
- Otherness is a nice point of view to noise elimination
- Pos, Named-Entity, Word-Cluster features based on diff sets



Cross-Language(Brain Hole)

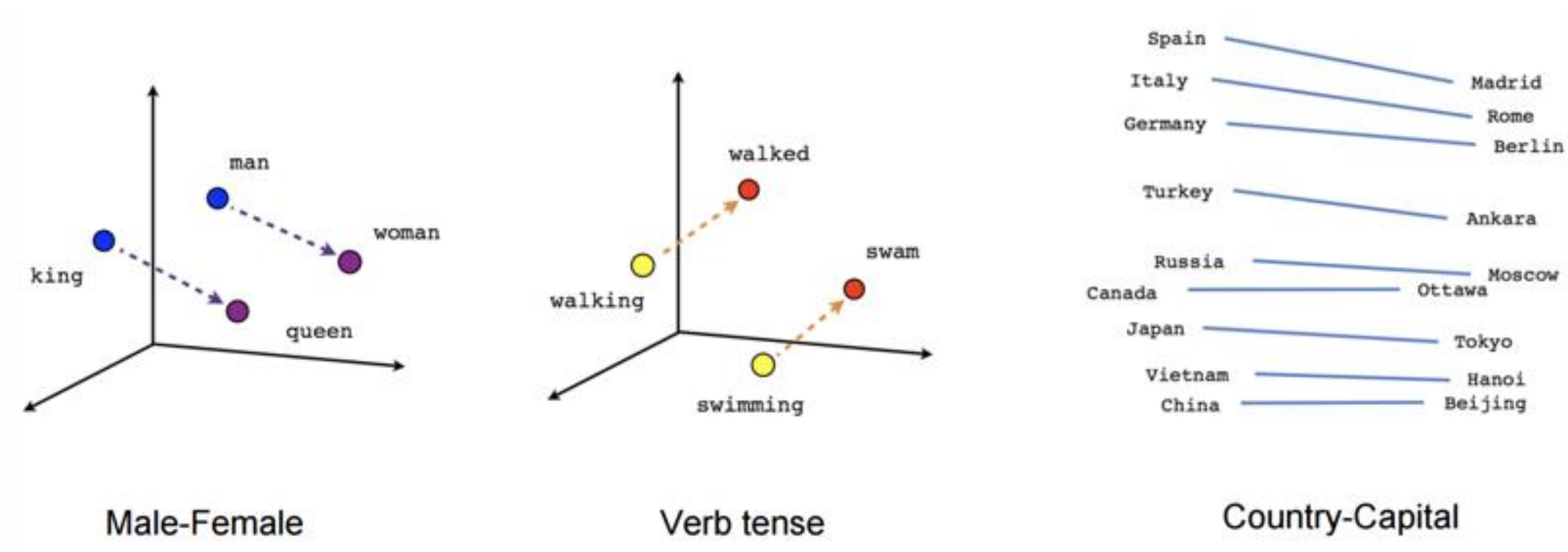
- Translate English to Chinese or other languages
- Same feature engineering repeat on translated languages
- Machine Translation are better on Polysemy and Unification



Representation Features

- Word Embedding
  - Latent Semantic Indexing (LSI)
  - Word2vec
  - Glove
- Sentence Embedding
  - Weighted Sum of Word Embedding
  - Paragraph Vector
  - Skip-Thought Vector

Word Representation



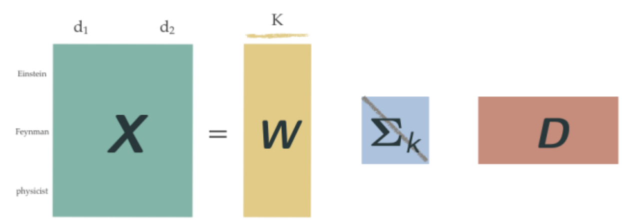
vector[Queen] = vector[King] - vector[Man] + vector[Woman]

- Semantically similar words are mapped to nearby points
- Efficient representation: continuous vector space

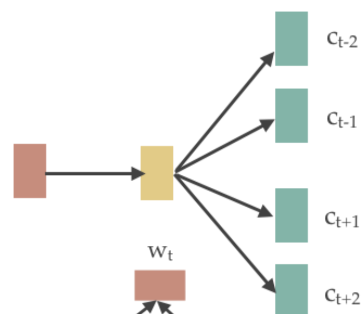
Word Representation

Context is the key in distributional hypothesis.
What type of context you use decides what kind of meaning or semantic relations between words you obtain.

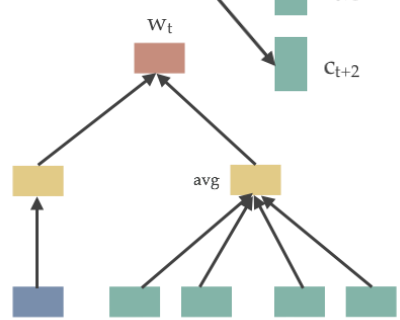
- LSI: SVD decomposition of **Word-Document** Co-occurrence Matrix



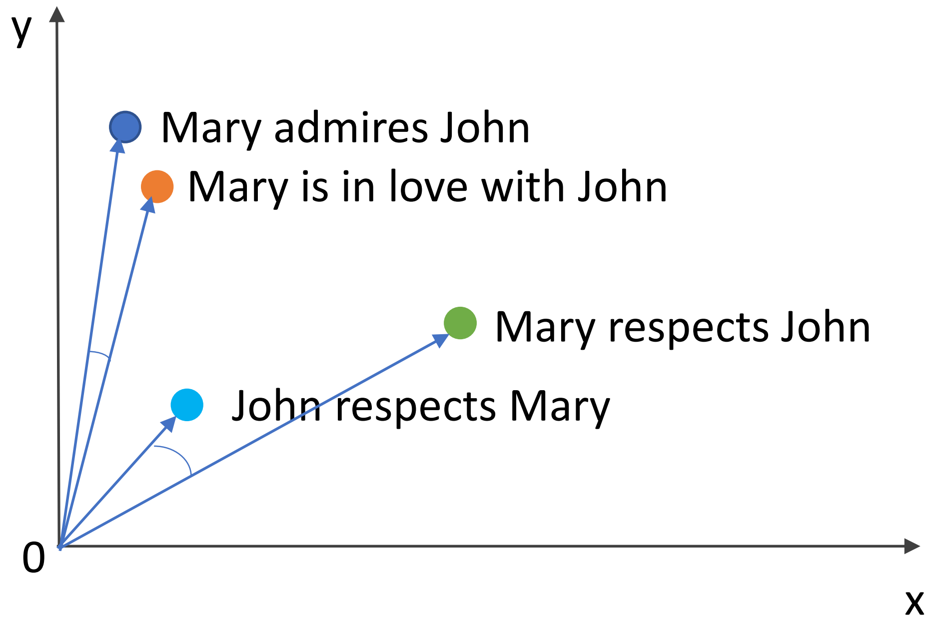
- Word2vec: word predict **local context** words.



- HDC: word predict **local context** & **global document** wide



Sentence Representation

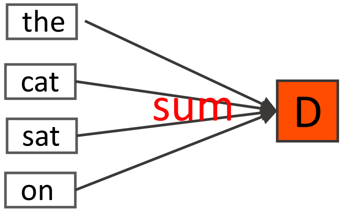


- Semantically similar sentence are mapped to nearby points
- Fluent & efficient representation:
  - Continuous vector space
  - Map varied-length sentence to fix-length vectors

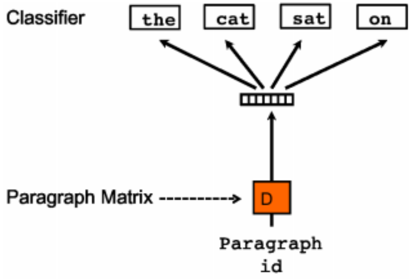
Sentence Representation

Internal word info. & **external** sentence info

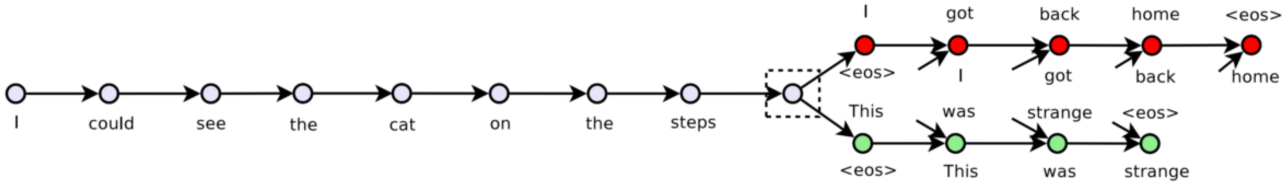
- Weighted Sum of Word Embeddings



- Paragraph Vector

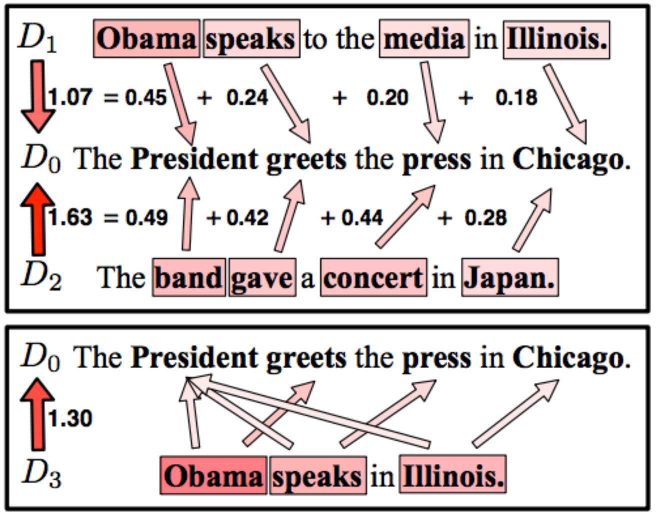


- Skip Thought



Representation Features

- Word vector features
  - Max matching signals
  - Word move distance
  - noun phrases similarities
- Sentence vector features
  - Cosine Similarity $\cos(\theta) = \frac{x \cdot y}{|x||y|}$
  - canberra $d = \sum_{k=1}^{n} \frac{|x_k - y_k|}{x_k + y_k}$
  - rmse_distance $d = \sqrt{\frac{\sum_{k=1}^{n}(x_k - y_k)^2}{n}}$
  - Minkowski (l = 1) : City Block/Manhattan $d = \sum_{k=1}^{n} |x_k - y_k|$
  - Minkowski (l = 2) : Euclidean $d = \sqrt{(x-y)(x-y)^T}$



Graph

- Build Graph
  - Directed Graph / Undirected Graph
  - Co-occurrence Based Graph / Similarity Based Graph
- Statistic of nodes and edges
  - In-degree of the nodes
- Structure information
  - Component analysis
  - Clique analysis
- Propagation information
  - PageRank / Hits
  - Neighbor analysis
  - Features propagation (shortest path)

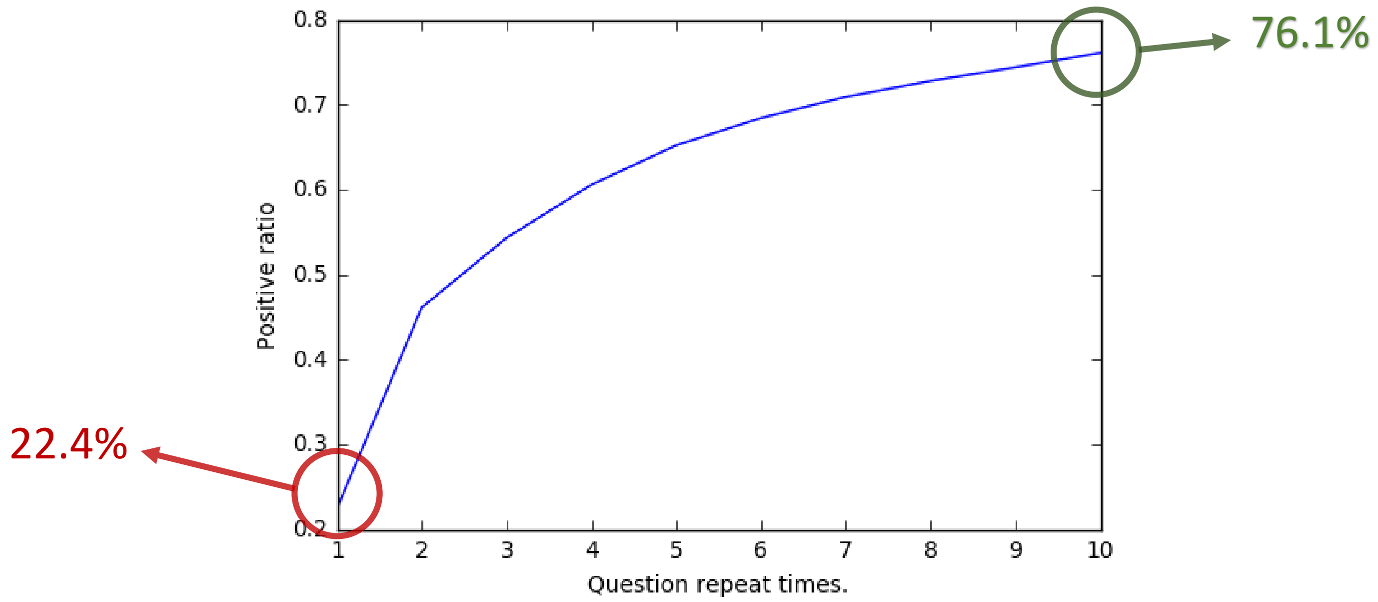
Build Graph

- Co-occurrence Based Graph
  - Node: Question
  - Edge: Question Pair in Train/Test dataset
  - Represent the **linking** properties of the questions.

- Similarity Based Graph
  - Node: Question
  - Edge: Similar Question Pairs evaluate by IR (BM25)
  - Represent the **similarity** properties of the questions.

Statistic of Nodes and Edges

- In-degree of the nodes
  - In Co-occurrence Based Graph, it is the same as the **repeat times** of each question in Train/Test set.

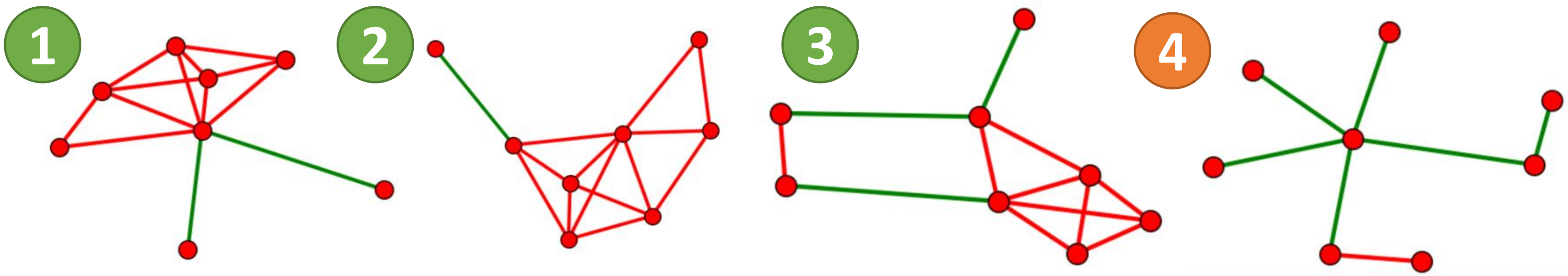


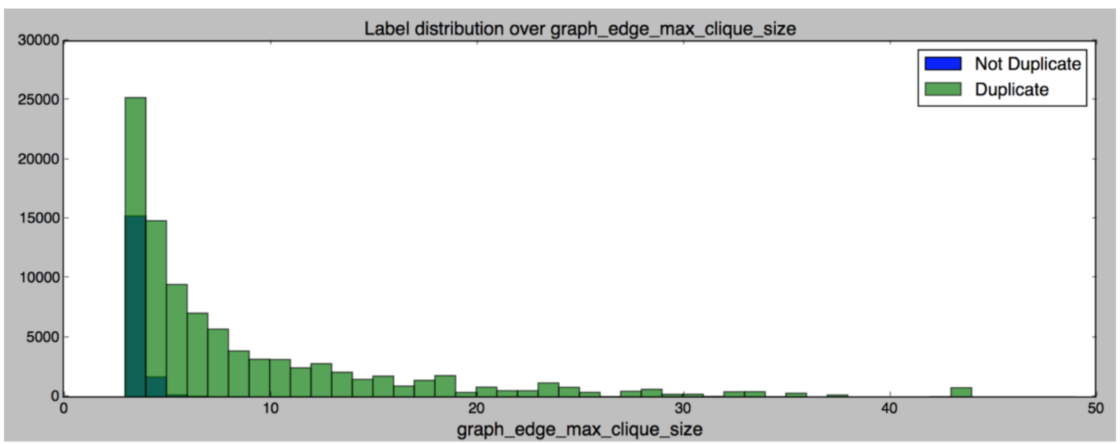
Explanation:

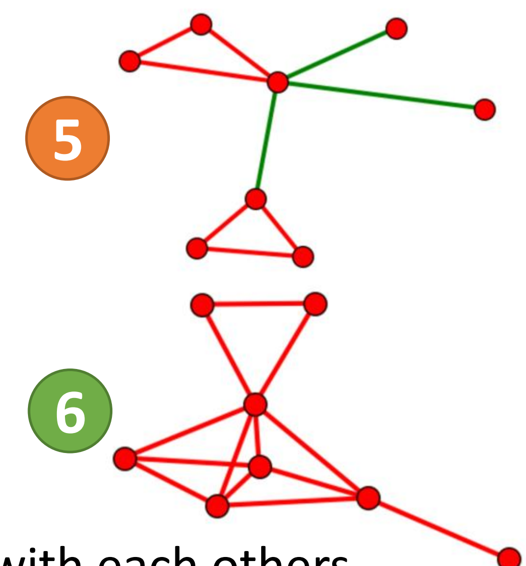
Frequent viewed questions = Hot topics = High duplicate ratio

Structure information

- Component & Clique analysis



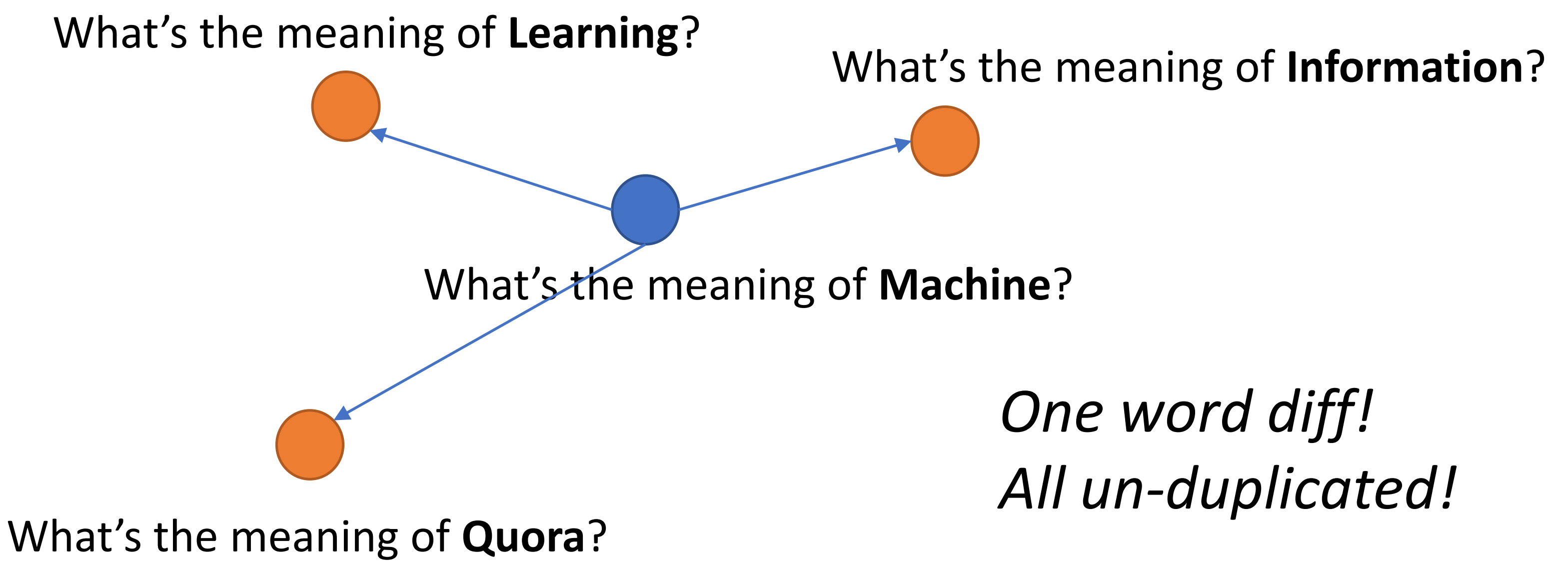




Explanation:
Different descriptions of the same question **link tightly** with each others.

Propagation Information

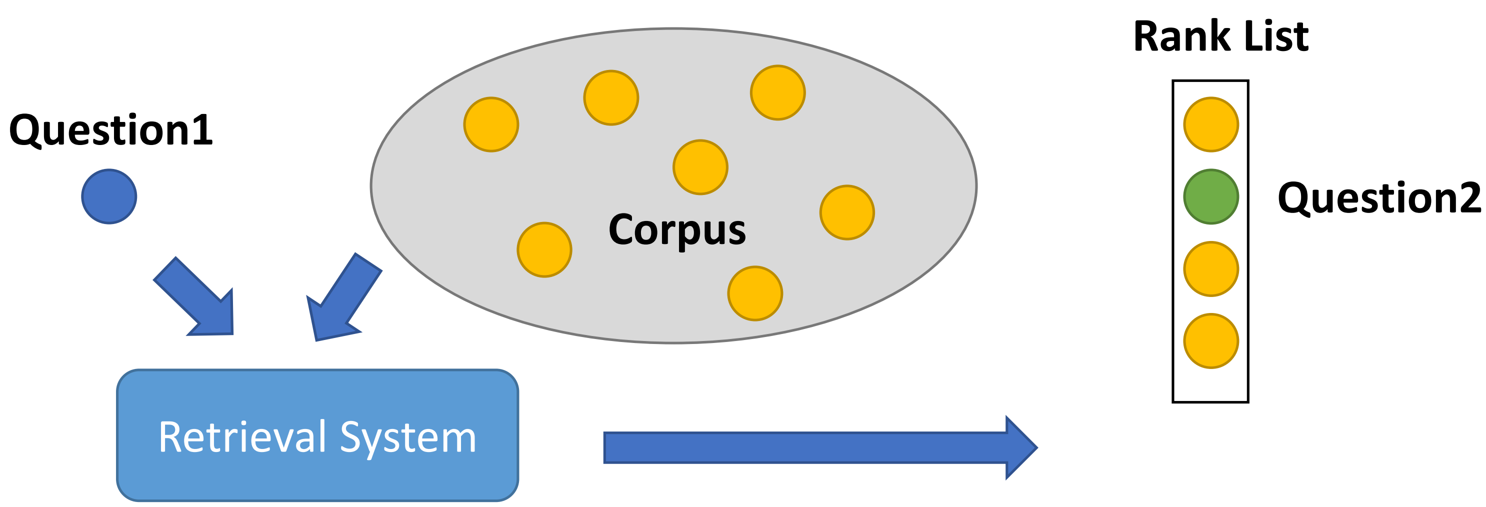
- Neighbor Analysis
  - In Co-occurrence Based Graph, neighbors' features can be used to represent current question.
  - Such as word shared count



One word diff!
All un-duplicated!

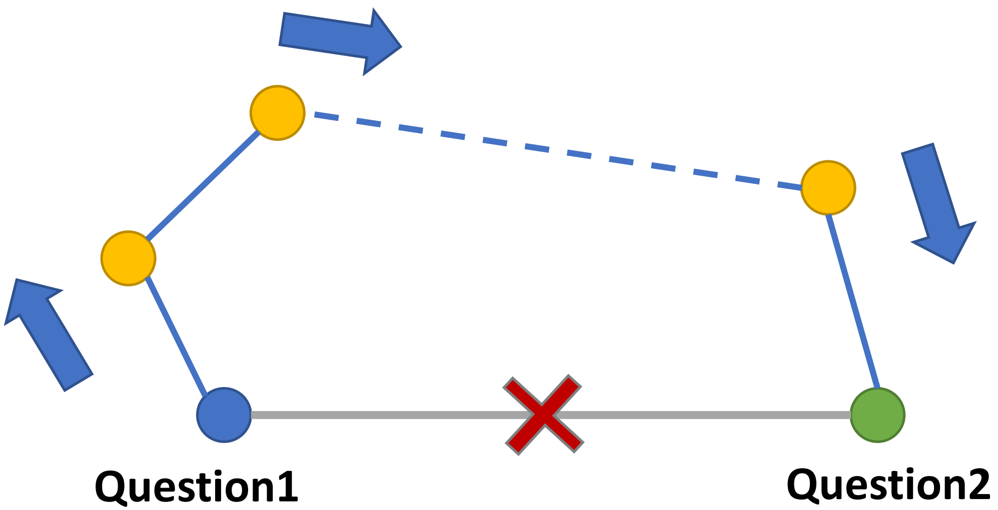
Propagation Information

- Neighbor Analysis
  - In Similarity Based Graph, the rank information of the neighbors are helpful.
  - We can treat the whole question set as a **corpus**, and the Quora System **retrieval/recommend** similar questions from corpus to users.



Propagation Information

- Feature Propagation
  - Put the feature value on the edge of the graph (Co-occurrence Based Graph).
  - Then calculate the shortest path value on the graph with removing current edge.



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Deep Models

- The text matching problem, in general, can be formalized as

$$\mathrm{Match}(T_1,T_2) = F(\phi(T_1),\phi(T_2))$$

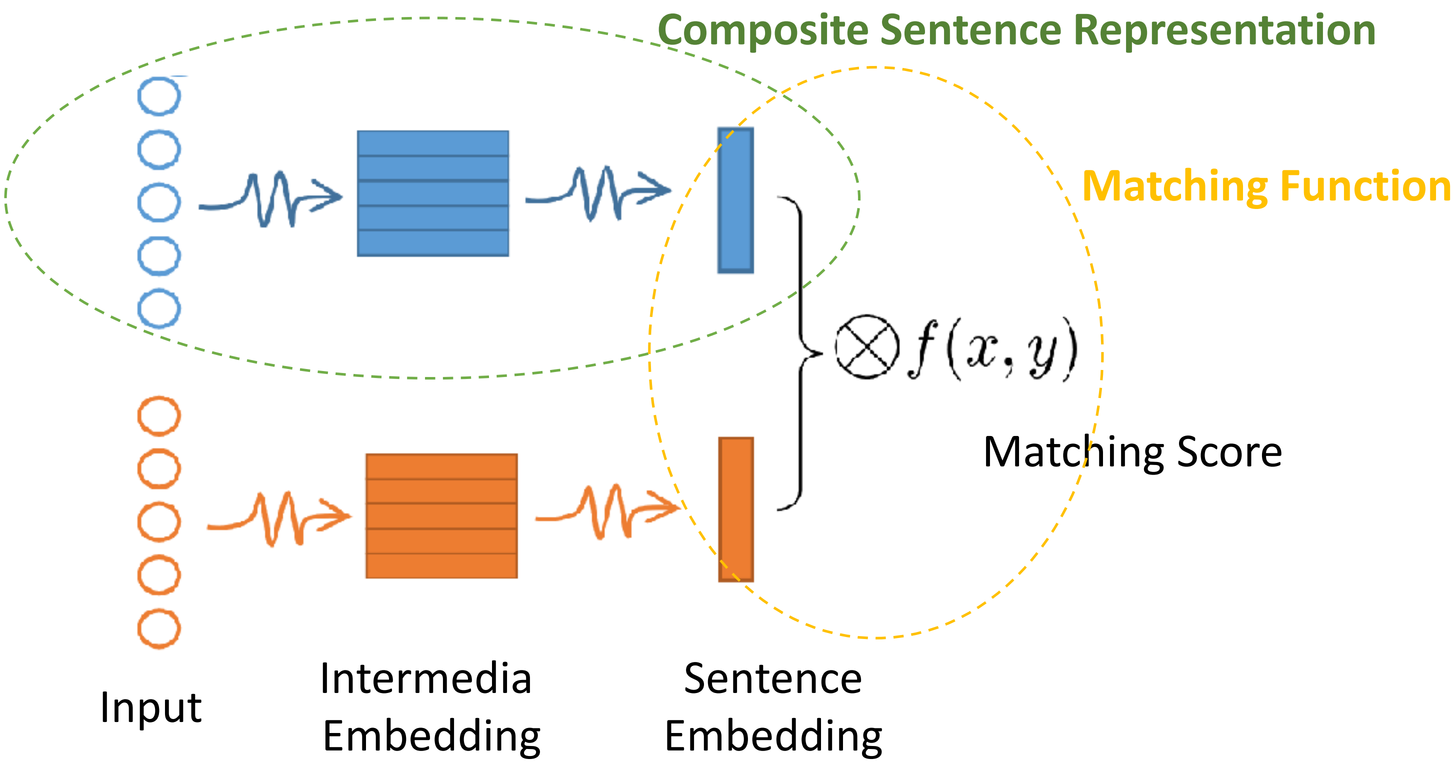
Scoring function based on the interaction between texts

Map each text to a representation vector

- Representation Based Models
- Interaction Based Models
- Best Single Deep Model

Representation Based Models

- Composite each sentence into one embedding
- Measure the similarity between two embeddings

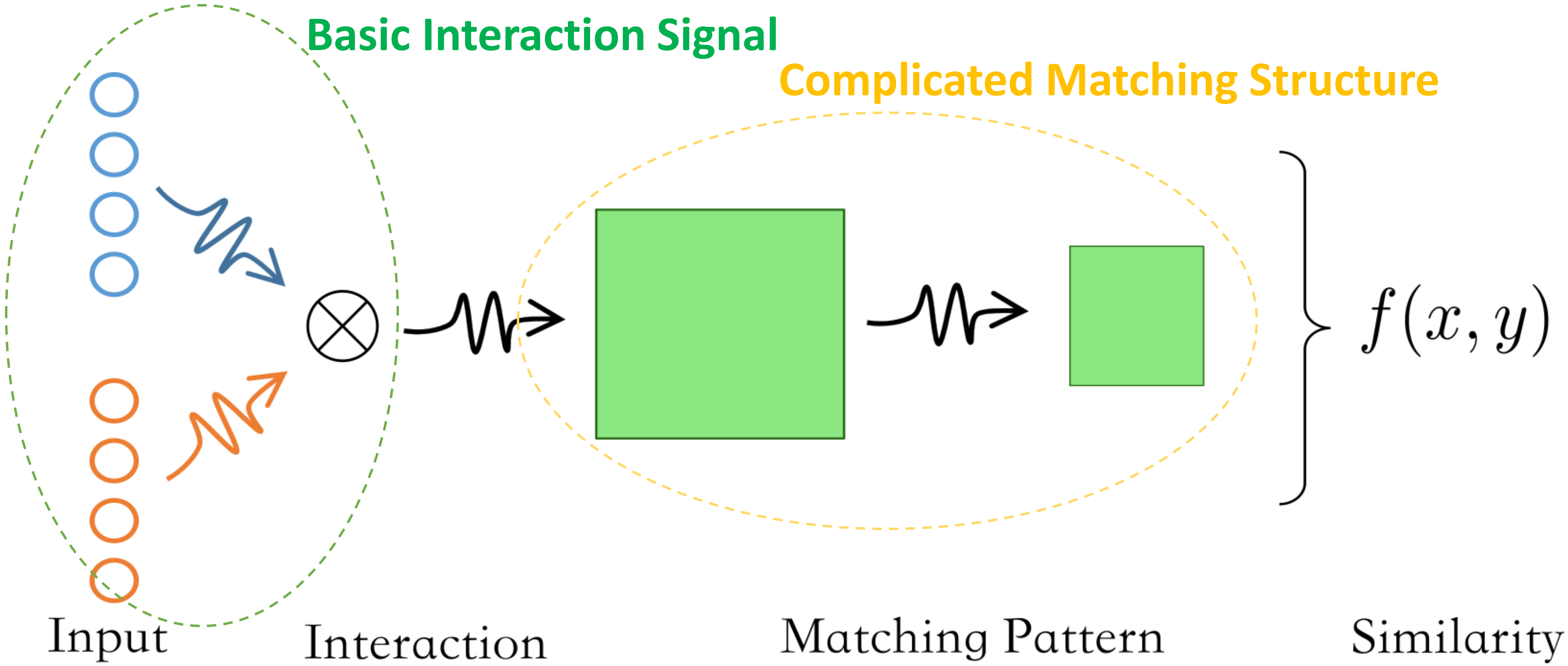


Typical Representation Based Models

- DSSM: Learning Deep Structured Semantic Models for Web Search using Click-through Data (Huang et al., CIKM’13)
- CDSSM: A latent semantic model with convolutional-pooling structure for information retrieval (Shen Y, He X, Gao J, et al. CIKM’14)
- ARC I: Convolutional Neural Network Architectures for Matching Natural Language Sentences (Hu et al., NIPS’14)
- **LSTM-RNN**: Deep Sentence Embedding Using the Long Short Term Memory Network: Analysis and Application to Information Retrieval (Palangi et al., TASLP’2016)

Interaction Based Models

- Two sentences meet before their own high-level representations mature
- Capture complex matching patterns

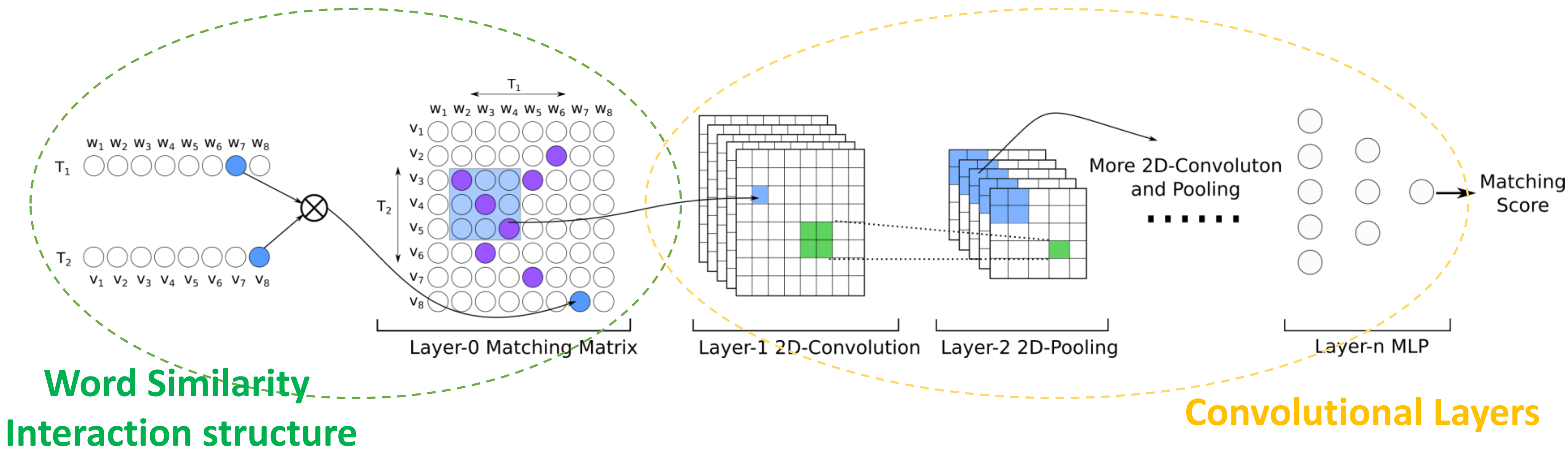


Typical Interaction Based Methods

- DeepMatch: A Deep Architecture for Matching Short Texts (Lu and Li, NIPS'13)
- ARC II: Convolutional Neural Network Architectures for Matching Natural Language Sentences (Hu et al., NIPS'14)
- **MatchPyramid**: Text Matching as Image Recognition. (Liang Pang, Yanyan Lan, Jiafeng Guo, Jun Xu, and Xueqi Cheng. AAAI 2016)
- **Match-SRNN**: Modeling the Recursive Matching Structure with Spatial RNN. (Shengxian Wan, Yanyan Lan, Jiafeng Guo, Jun Xu, and Xueqi Cheng. IJCAI 2016)

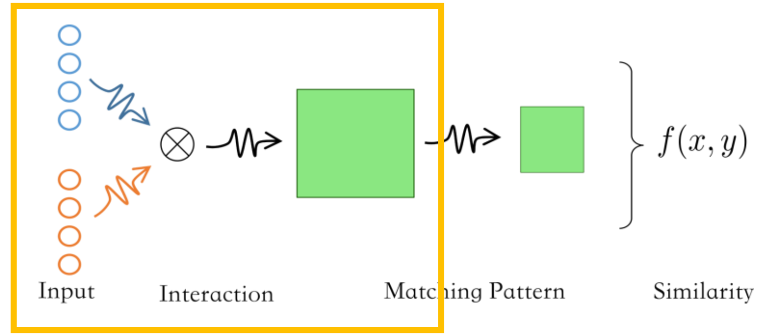
MatchPyramid

- Inspired by image recognition task
- Part 1: Construct Matching Matrix
- Part 2: Hierarchical Convolution



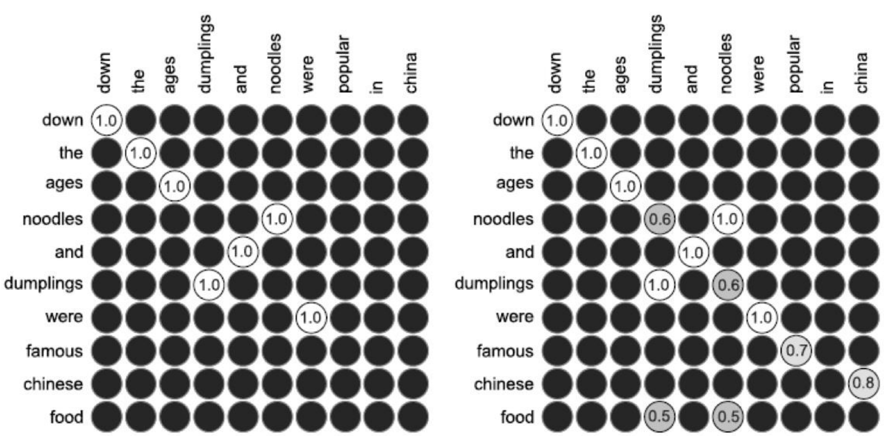
Pang L, Lan Y, Guo J, et al. Text matching as image recognition//Proceedings of the 30th AAAI Conference on Artificial Intelligence. Phoenix, USA, 2016: 2793-2799.

MatchPyramid
- Matching Matrix

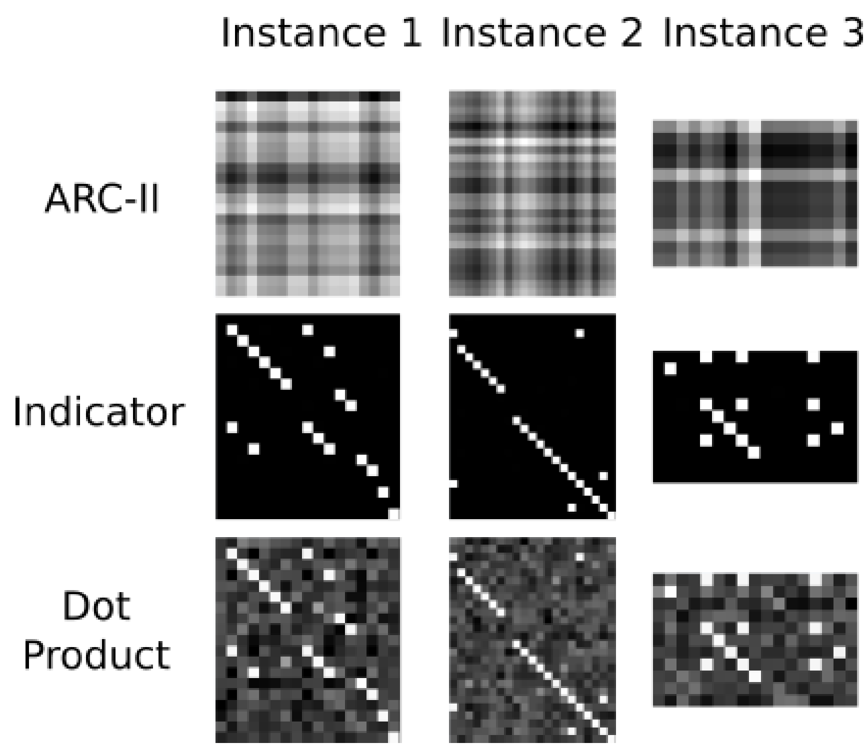


- Bridging the Gap between Text Matching and Image Recognition.

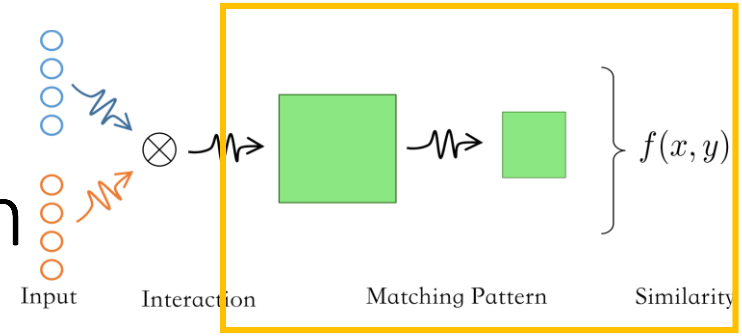
$$\mathbf{M}_{ij} = w_i \otimes v_j$$



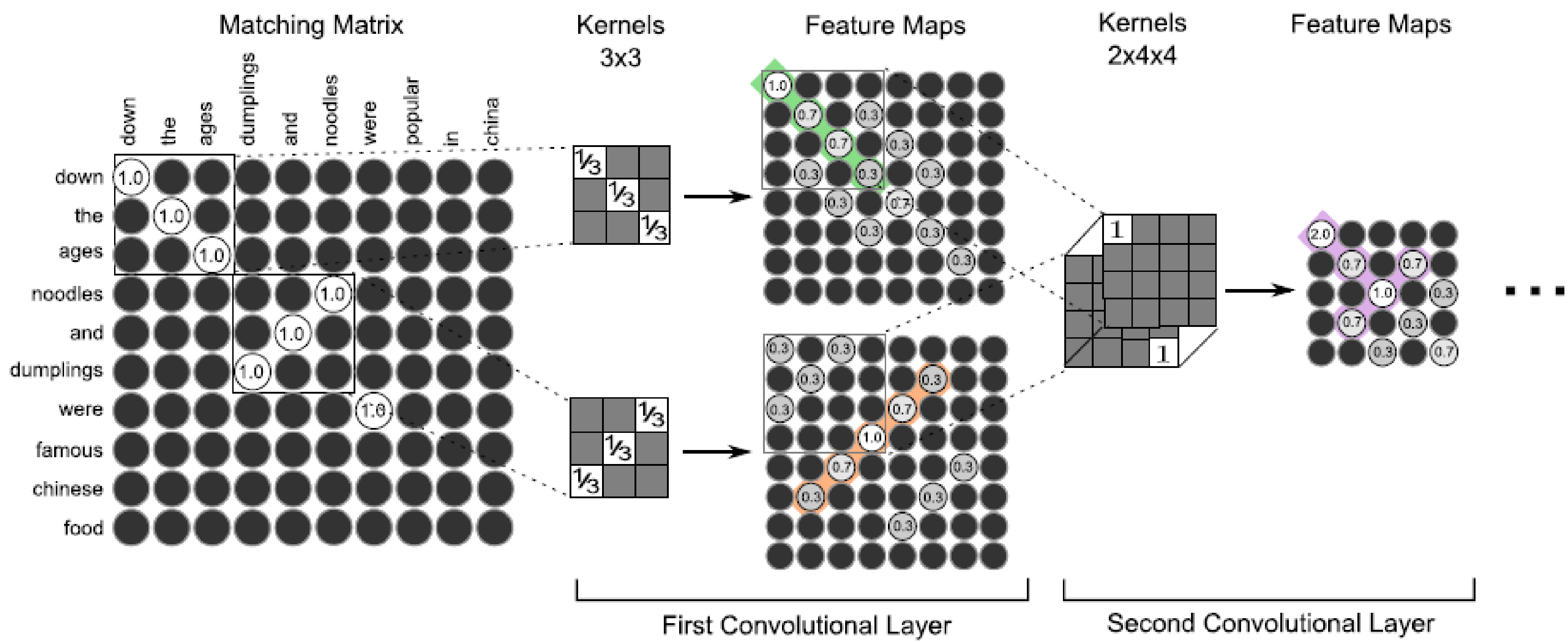
(a) Matching Matrix-Indicator (b) Matching Matrix-Cosine



MatchPyramid
- Hierarchical Convolution

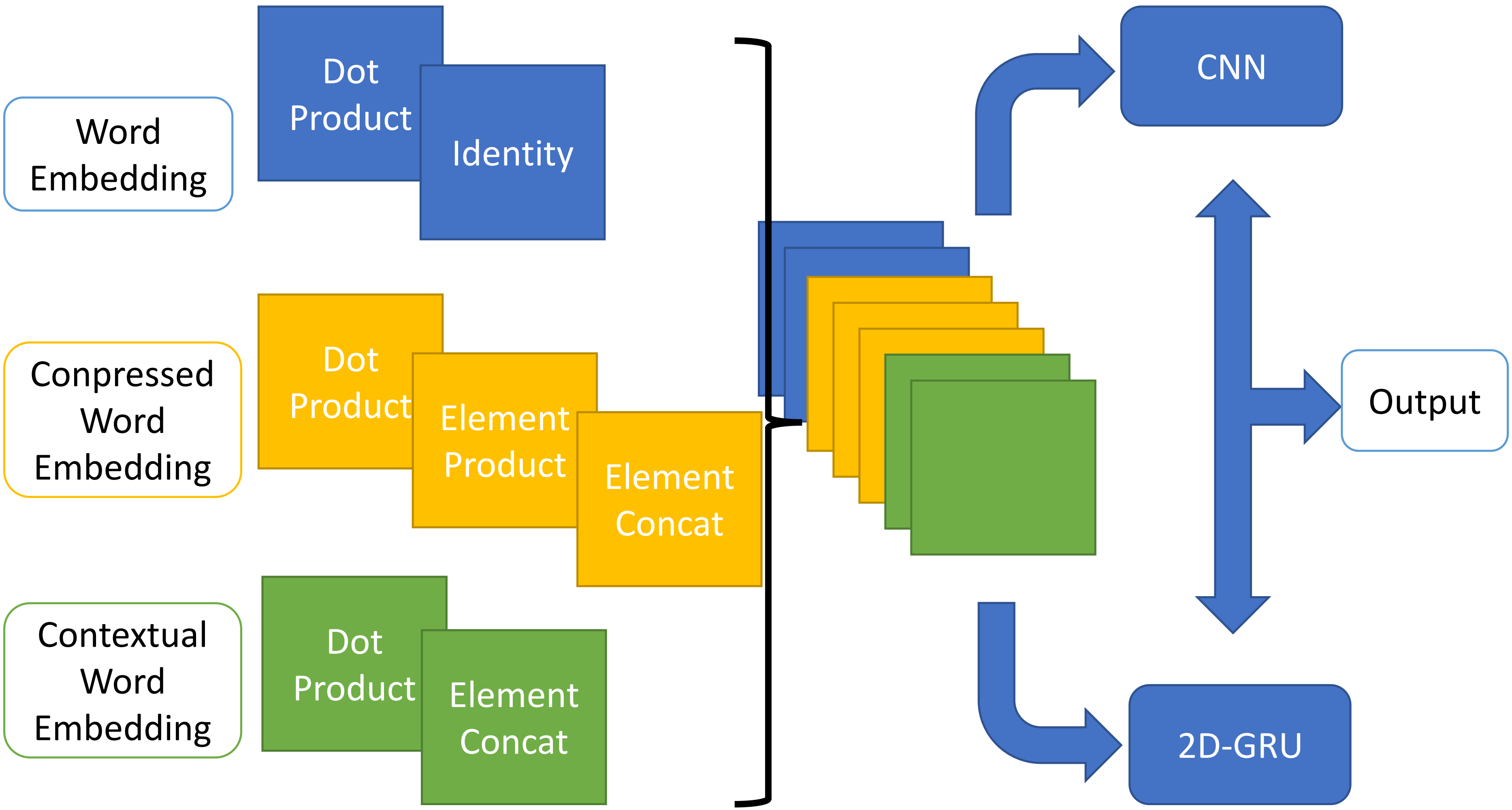


- A way to capture rich matching patterns

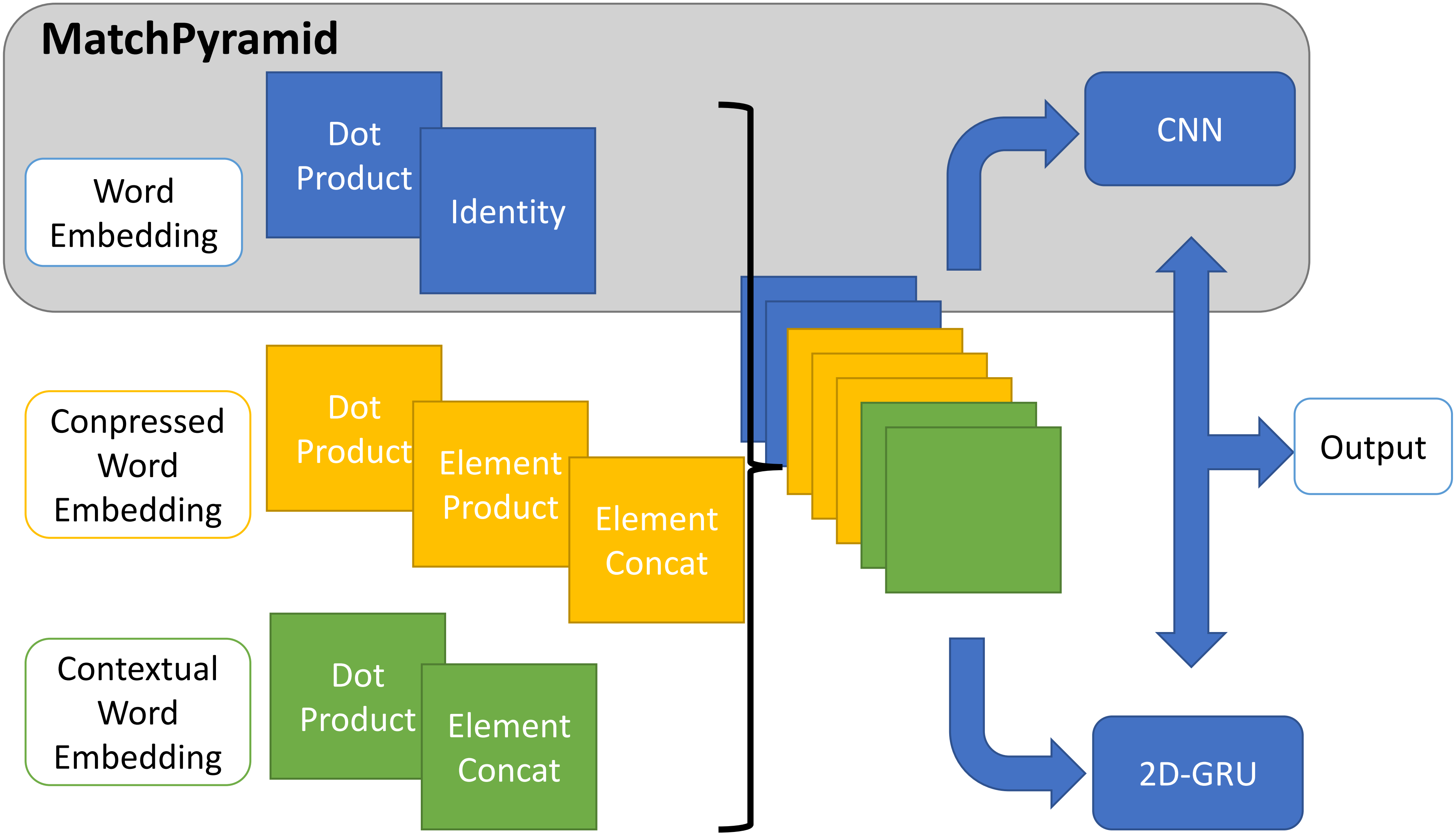


Best Single Deep Model

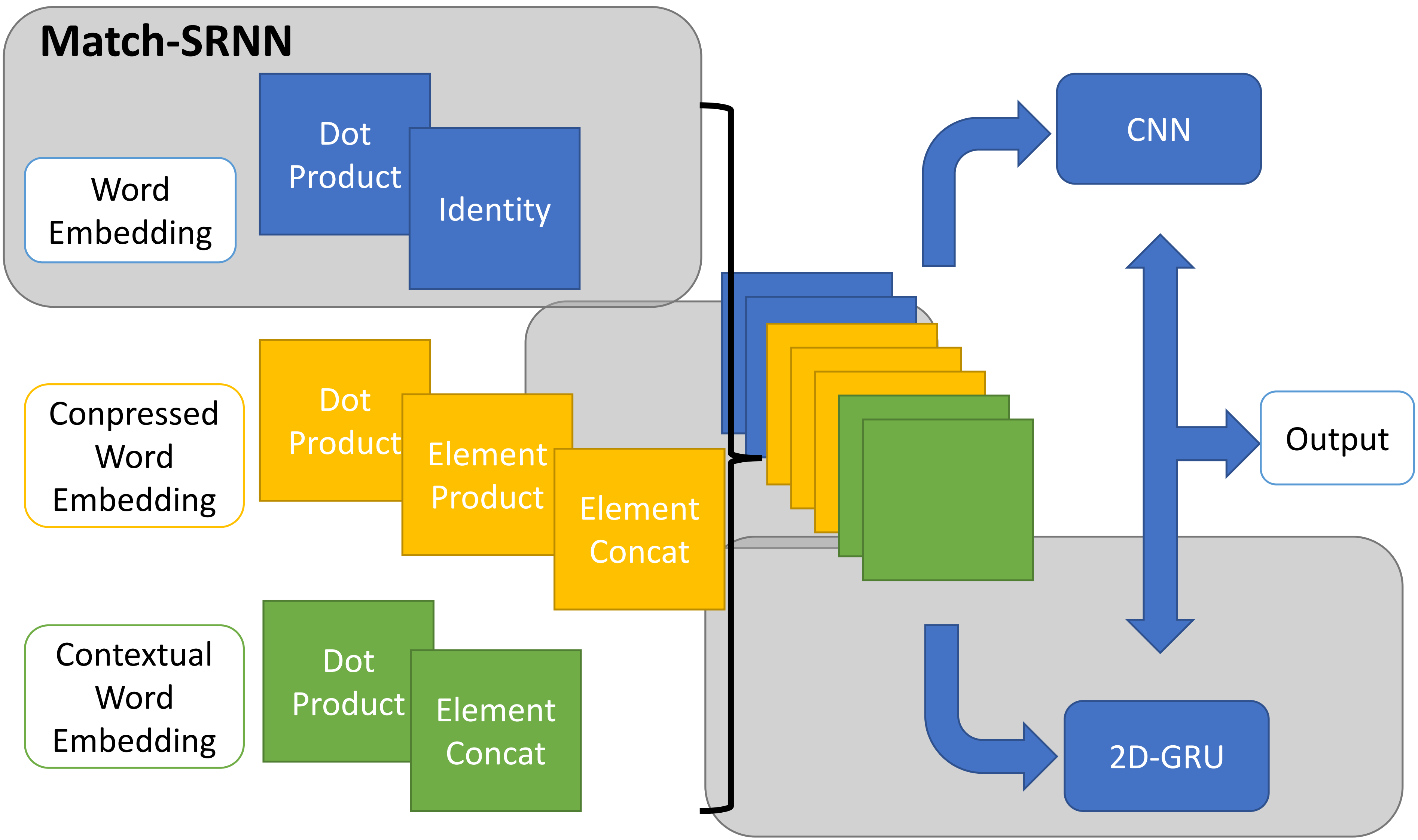
Combine of MatchPyramid, Match-SRNN and MVLSTM.



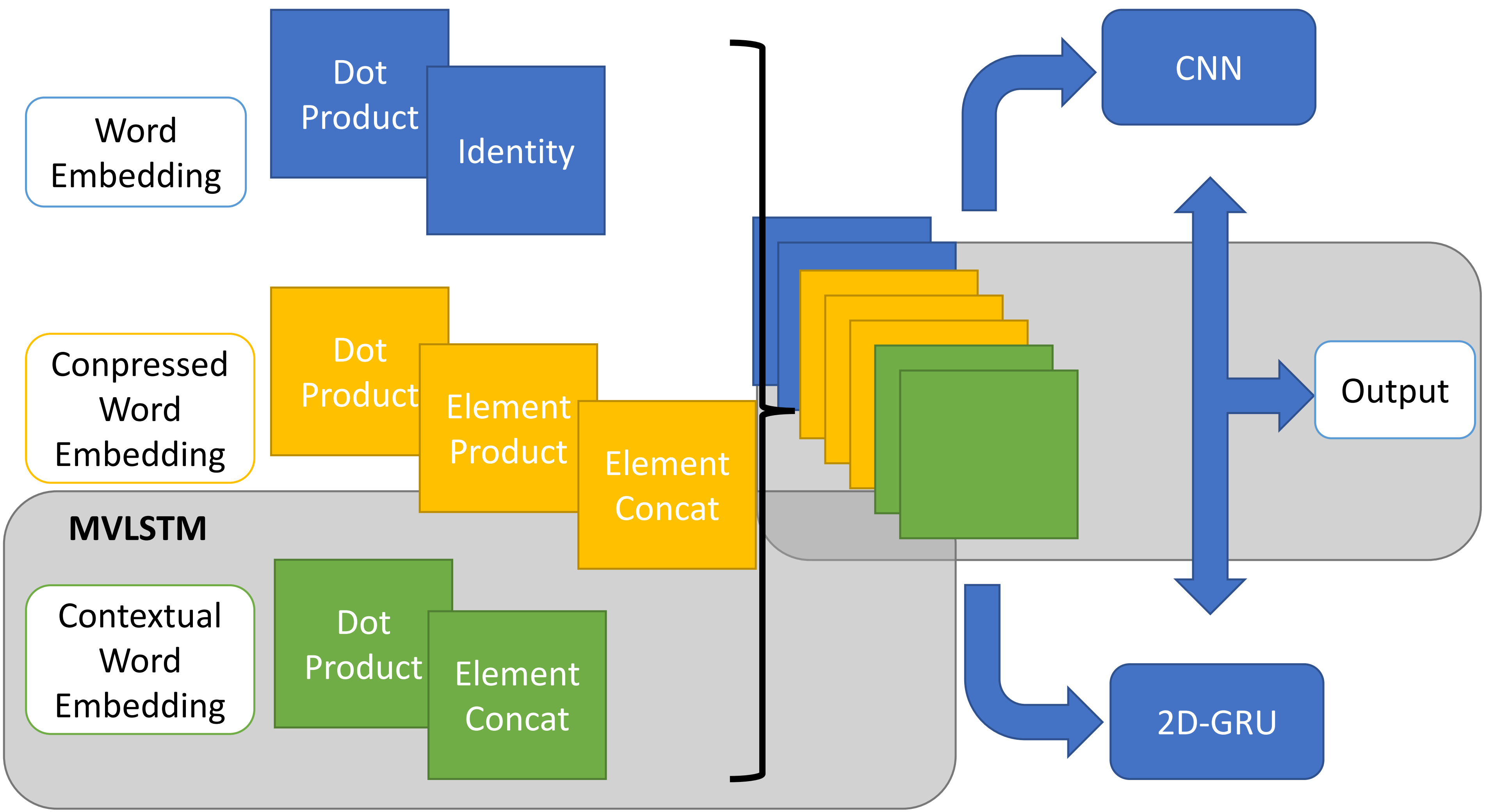
Best Single Deep Model



Best Single Deep Model



Best Single Deep Model



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  - **Traditional Model**
  - Stacking
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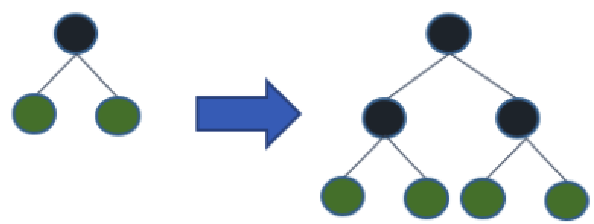
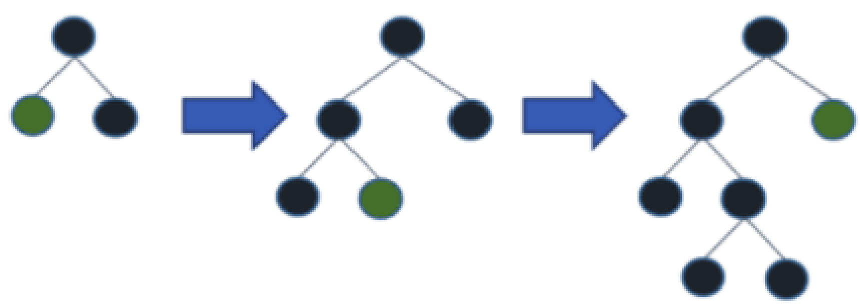
Boosting Models

- XGBoost(level-wise)



- LightGBM(leaf-wise)



- LGB is faster than XGB without lossing performance

Boosting Models

- Feature Selection
  - Low Dimension Dense Features(1500 dim)
  - Not sensitive to high dim features and may influence training speed

- Dart Mode
  - Not sensitive to a single tree learner
  - Increase diversity of each model

Factorization Machine

$$\hat{y}(\mathbf{x}) := w_0 + \sum_{i=1}^{n} w_i \, x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \langle \mathbf{v}_i , \mathbf{v}_j \rangle \, x_i \, x_j$$

Linear Part

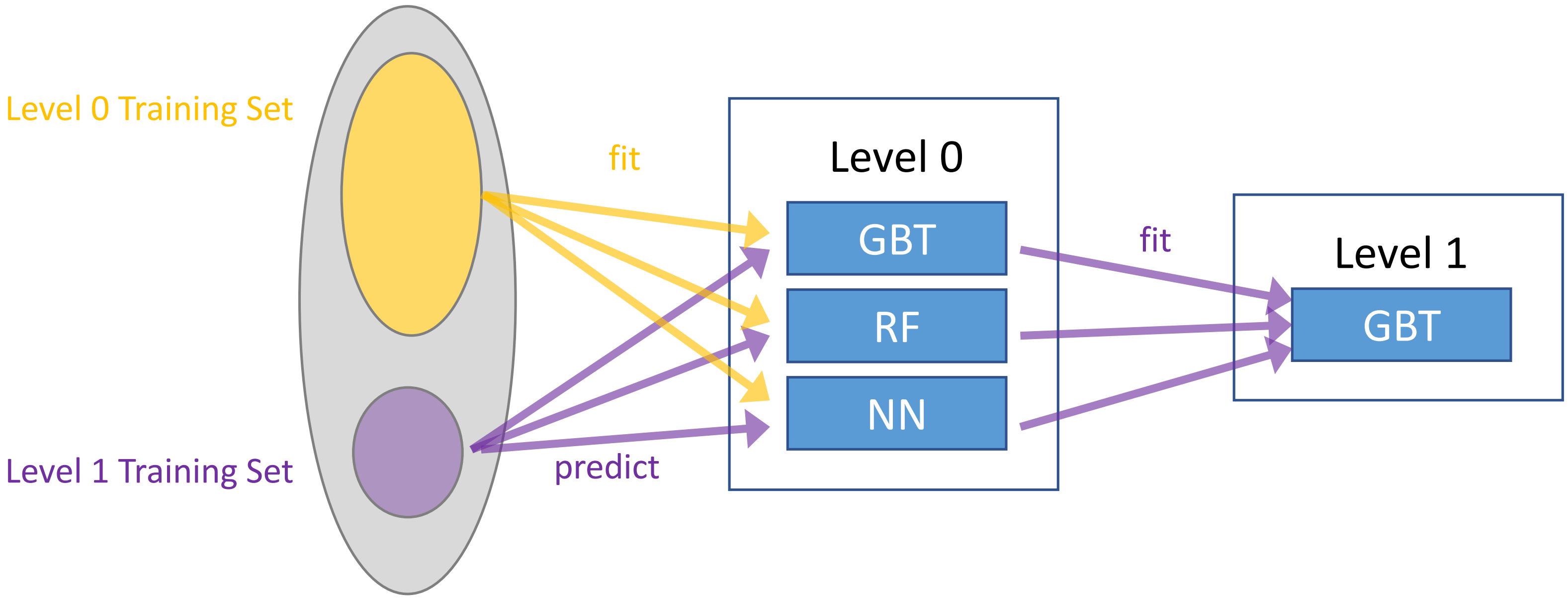
Second-order
non-linear Info

- Extract Linear and Second order interaction extra info
- Apply to 1.5 million sparse features
- Sensitive to feature scale, must normalization or hash bin.

Content

Traditional Stacking

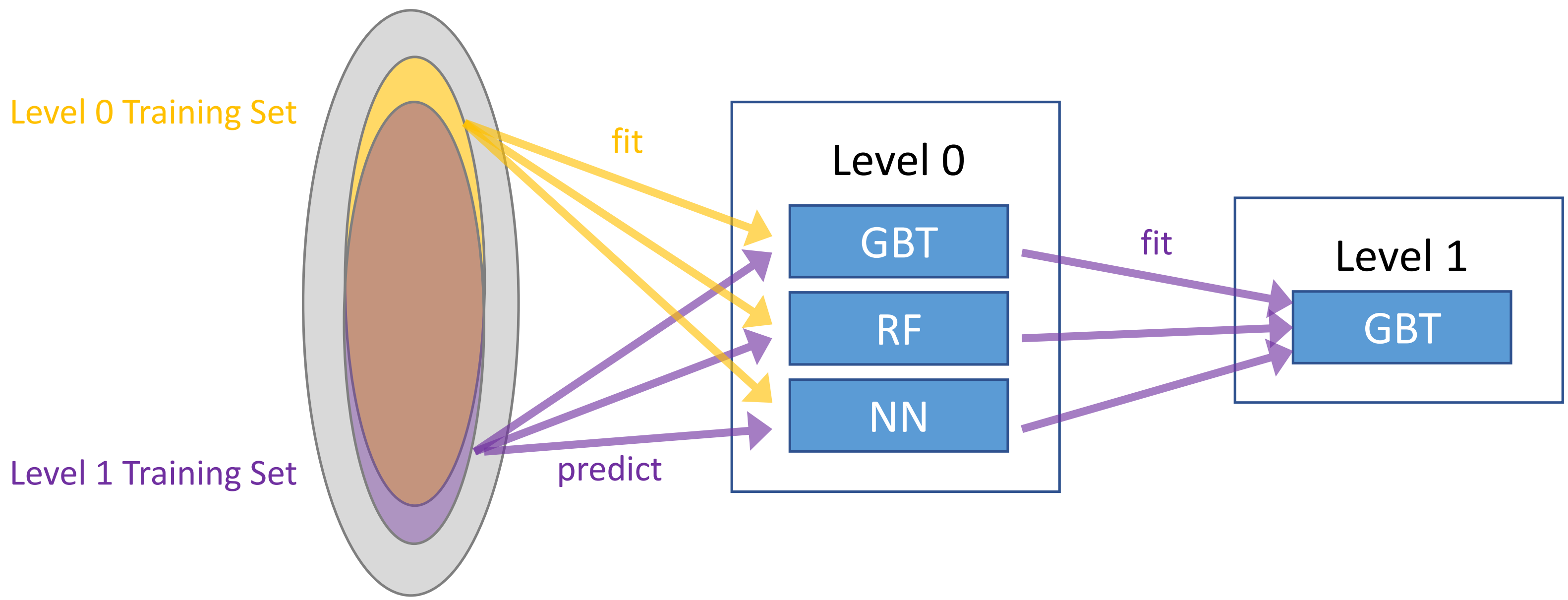
- Split the training set into two **disjoint** sets.
- **Train** several base learners on the first part and **Test** the base learners on the second part.



Deep Fusion

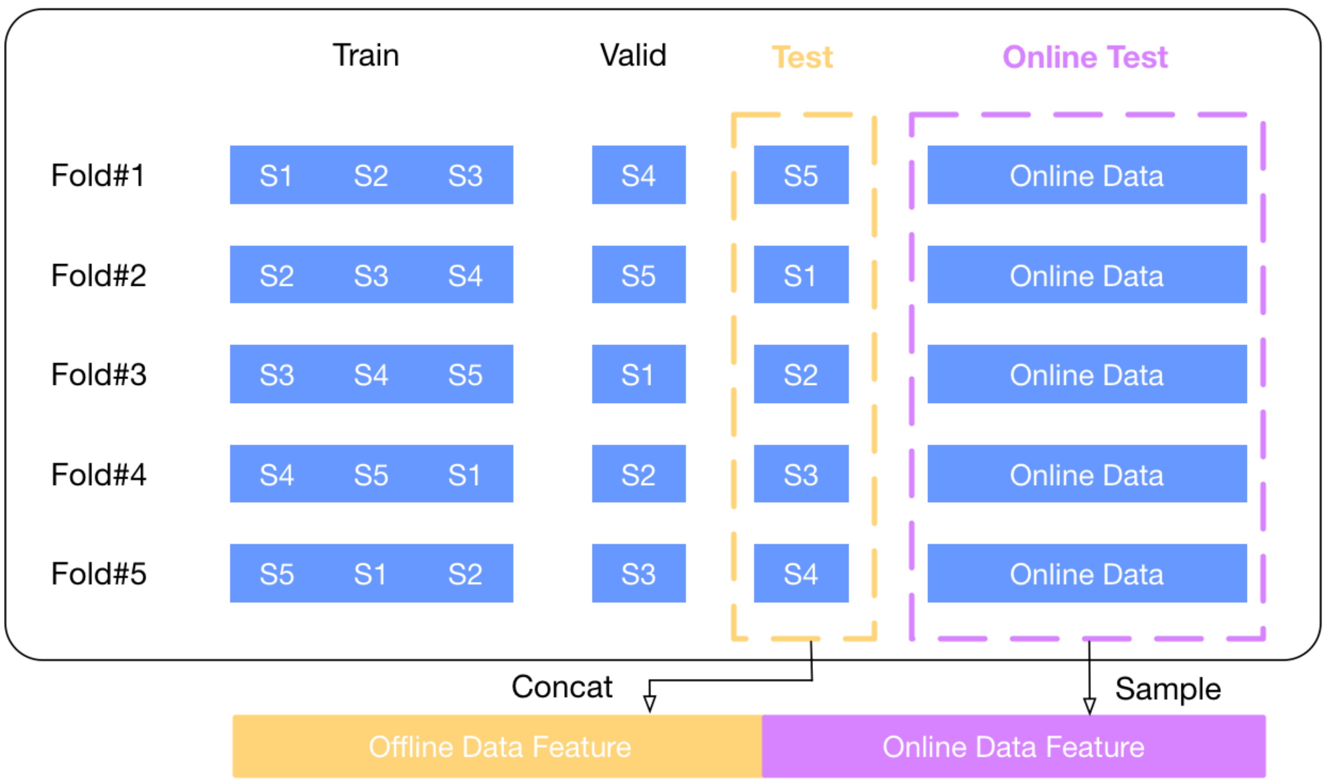
CHALLENGE

- How to **combine** good results and bad results?
- How to use information of **complete** set?



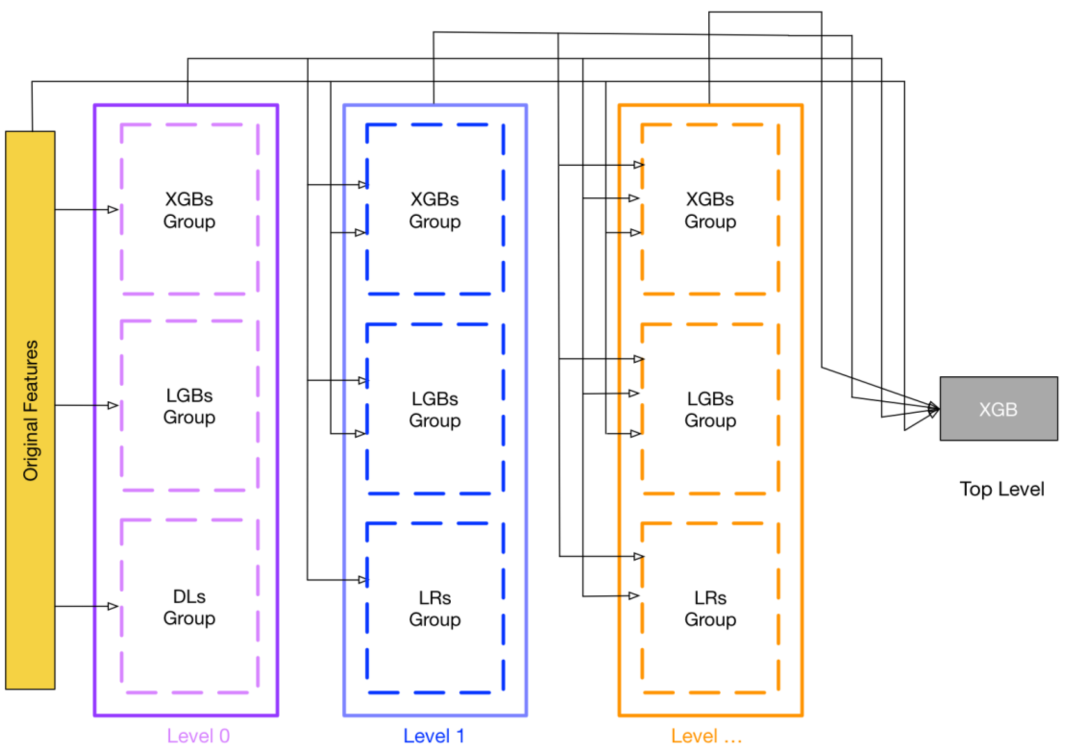
Deep Fusion • **Single Stacking**

1. Fit and make predictions with specified model 5 times.
2. Make prediction for online data 5 times with models generated in previous step.



Deep Fusion • **Cascade Stacking**

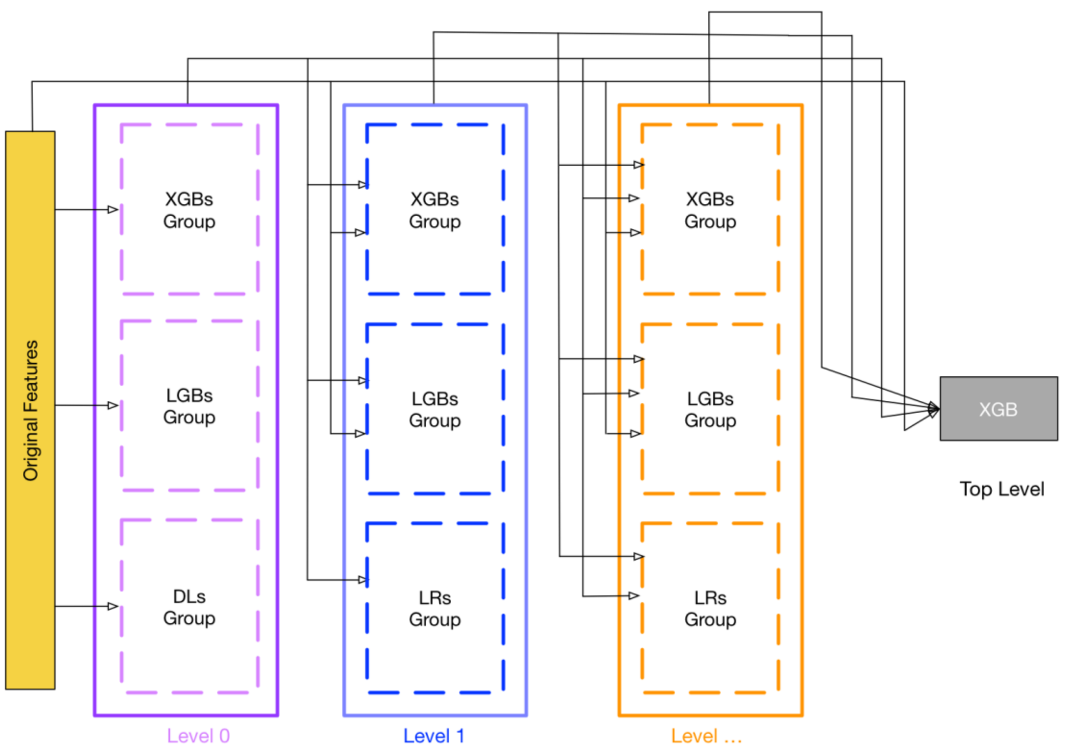
1. Fit and make predictions based on original features with diverse models.
2. Fit and make predictions based on **all** of the transformed features and **original** features with diverse models.



Deep Fusion • **Cascade Stacking**

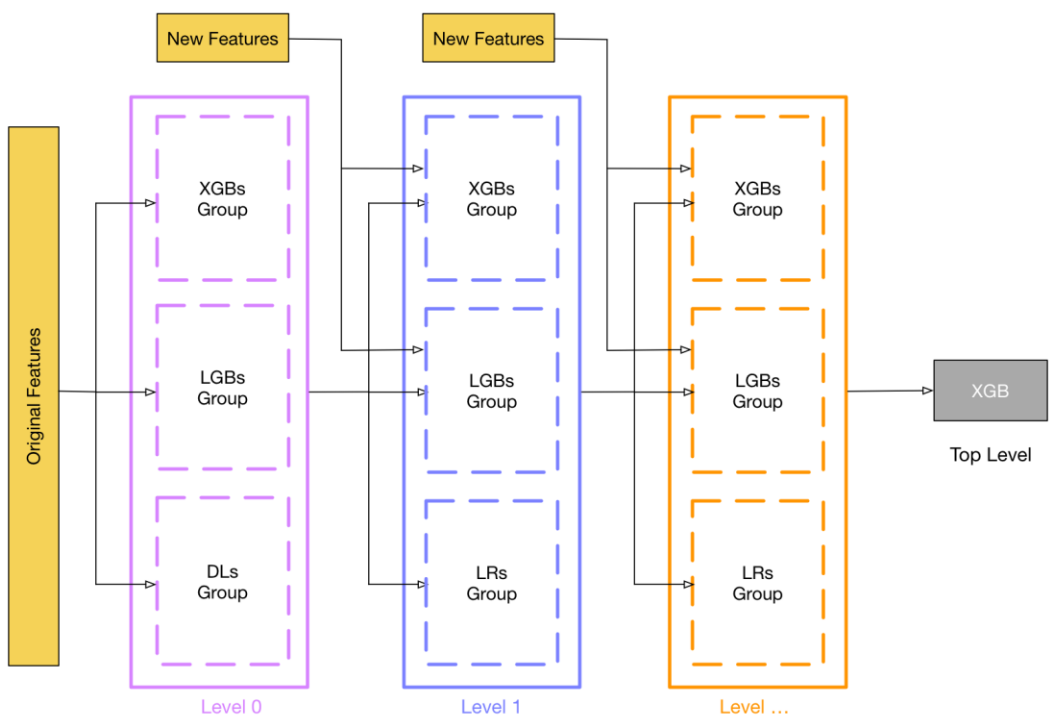
CHALLENGE

- The rebuilding process is extremely **time consuming**.
- The construction of the model is **mainly** based on the transformed features



Deep Fusion • **Hierarchical Stacking**

1. Fit and make predictions based on original features with diverse models.
2. Fit and make predictions based on **last layer** transformed features and **new extracted features** with diverse models.



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Post-processing

CHALLENGE

- The **distribution** of the offline data set (train.csv) and online data set (test.csv) are quite different.
- There are lots of **fake data points** in the online data set.

offline data set

online data set

Post-processing • **Split**

The standards of the division:

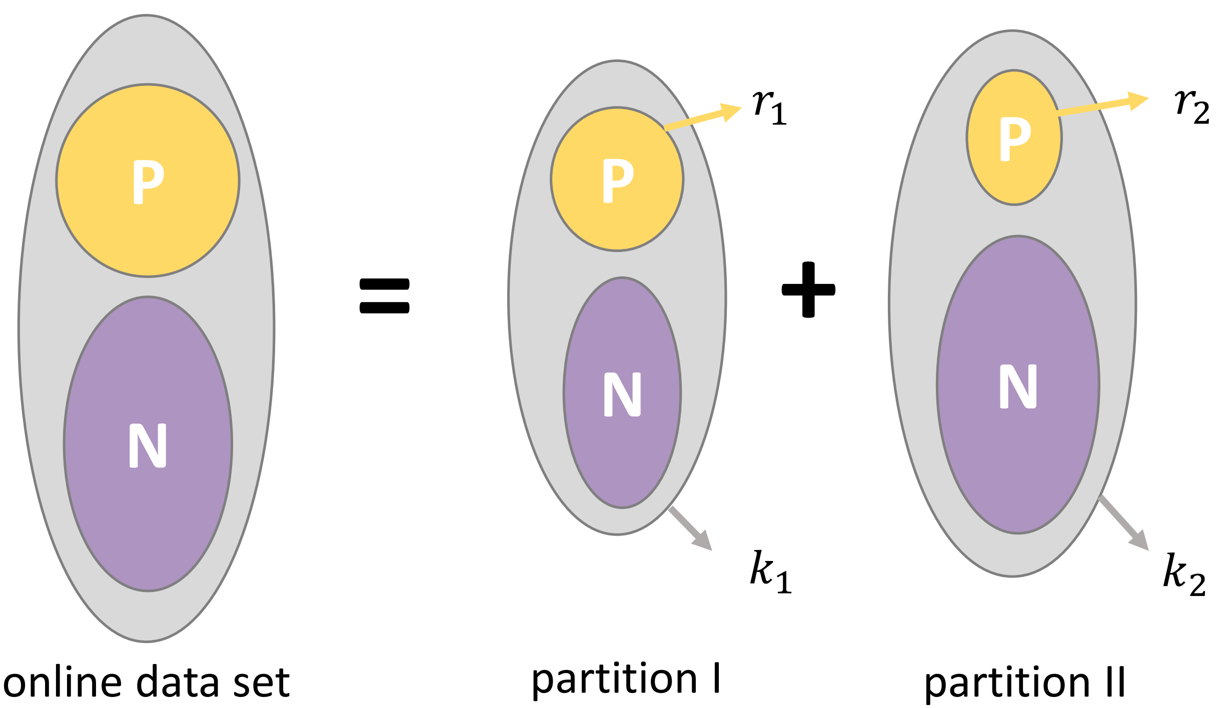
- graph_edge_max_clique_size (mc_size): Number of nodes contained in the largest clique of the edge.
- graph_edge_cc_size (cc_size): Number of nodes contained in the connected component of the edge.

	$mc\_size < 3$ $cc\_size < 3$	$mc\_size < 3$ $cc\_size \geq 3$	$mc\_size = 3$	$mc\_size > 3$
train.csv	118,065	173,164	40,482	72,579
test.csv	1,933,597	344,283	23,841	44,075

Post-processing · **Split**

- Solve the nonlinear equations to obtain the true data ratio and positive samples ratio of different parts for online data.

$$\mathrm{k}_1(r_1 \log v_{11} + (1 - r_1)\log v_{10}) + k_2(r_2 \log v_{21} + (1 - r_2)\log v_{20}) = -\mathrm{score}$$



Post-processing · **Split**

- Change the value of $v_{11}, v_{10}, v_{21}, v_{20}$ and corresponding scores to construct nonlinear equations.

Table 3: Data Ratio of Different Parts

	$mc\_size < 3$ $cc\_size < 3$	$mc\_size < 3$ $cc\_size \geq 3$	$mc\_size = 3$	$mc\_size > 3$
train.csv	29.20%	42.83%	10.01%	17.95%
test.csv	30.50%	52.19%	6.08%	11.24%

Table 4: Positive Sample Ratio of Different Parts

	$mc\_size < 3$ $cc\_size < 3$	$mc\_size < 3$ $cc\_size \geq 3$	$mc\_size = 3$	$mc\_size > 3$
train.csv	23.35%	14.95%	62.32%	97.26%
test.csv	5.74%	4.50%	40.88%	96.50%

Post-processing • **Rescale**

- Only difference between two distributions is they happen to have different proportions of positives and negatives.

$$X|(y=0) \sim X'|(y'=0) \quad \text{AND} \quad X|(y=1) \sim X'|(y'=1)$$

1st step

$$\begin{aligned} p \approx \mathbb{P}(y|x) &= \frac{\mathbb{P}(x|y)\mathbb{P}(y)}{\mathbb{P}(x)} \\ &= \frac{\mathbb{P}(x|y)\mathbb{P}(y)}{\mathbb{P}(x|y)\mathbb{P}(y) + \mathbb{P}(x|\neg y)\mathbb{P}(\neg y)} \\ &= \frac{u}{u+v}, \end{aligned}$$

Post-processing • **Rescale**

- Only difference between two distributions is they happen to have different proportions of positives and negatives.

$$X|(y=0) \sim X'|(y'=0) \quad \text{AND} \quad X|(y=1) \sim X'|(y'=1)$$

2st step

$$\begin{aligned} p' \approx \mathbb{P}(y'|x) &= \frac{\mathbb{P}(x|y')\mathbb{P}(y')}{\mathbb{P}(x|y')\mathbb{P}(y') + \mathbb{P}(x|\neg y')\mathbb{P}(\neg y')} \\ &= \frac{\alpha u}{\alpha u + \beta v}. \end{aligned}$$

Post-processing • **Rescale**

- Rescale the prediction results in different parts seperately based on prior knowledge.

positive samples rate on online data set

Derive

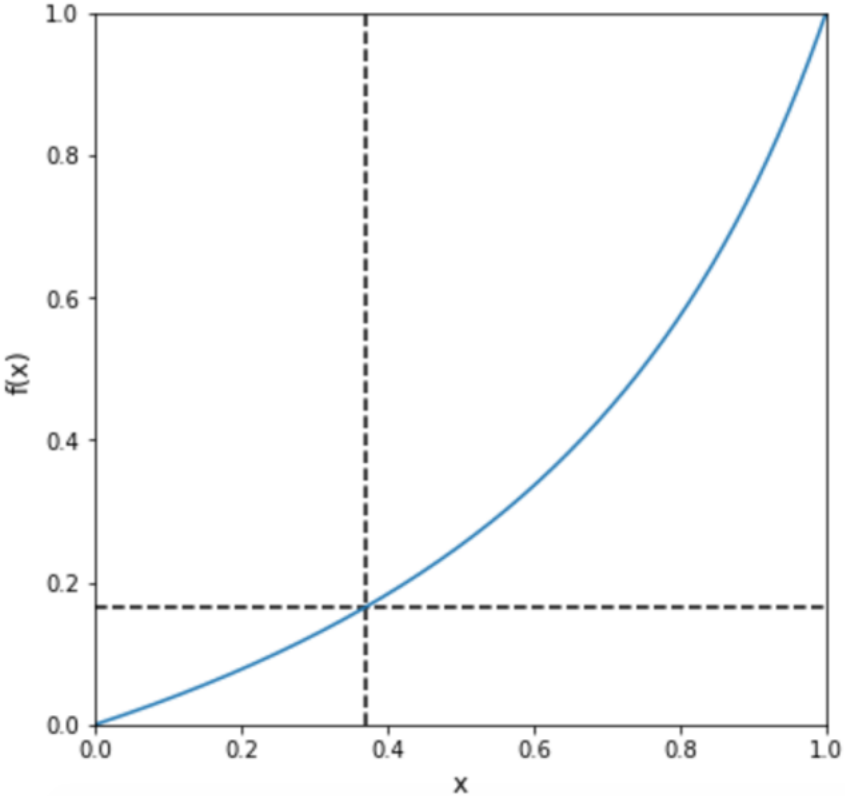
$$y_{rescale} = \frac{\frac{r_{online}}{r_{offline}} * y}{\frac{r_{online}}{r_{offline}} * y + \frac{1 - r_{online}}{1 - r_{offline}} * (1 - y)}$$

original values of prediction

positive samples rate on offline data set

Post-processing • **Rescale**

- Rescale the prediction results in different parts separately based on prior knowledge.



FeatWheel • **Characteristics**

- Developed a light weight Machine Learning framework to finish feature extraction, feature merging and so on.

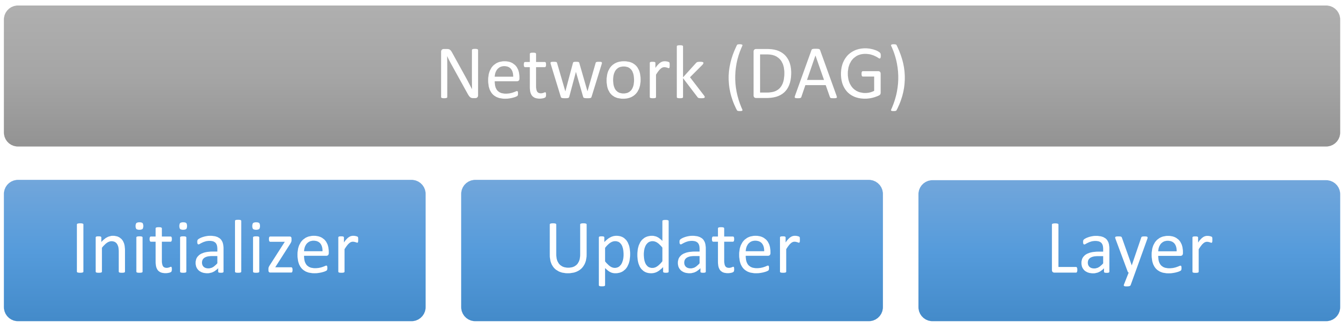
S Simple:
focus on extracting features and write a config file

F Flexible:
specify the features you need and auto finish feature merging

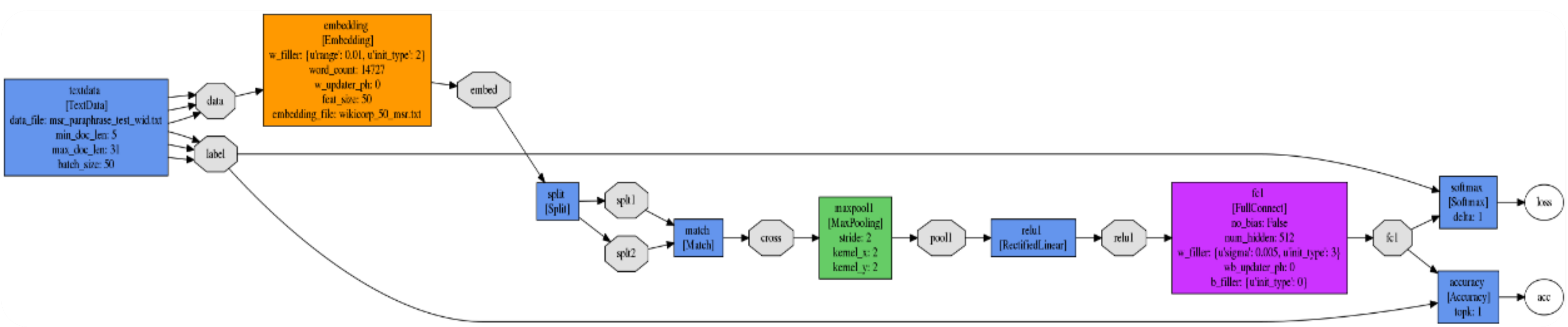
E Efficient:
generate index files to split the data set into training, validation and test

R Reliable:
generate a separate output directory to keep the operating environment

TextNet



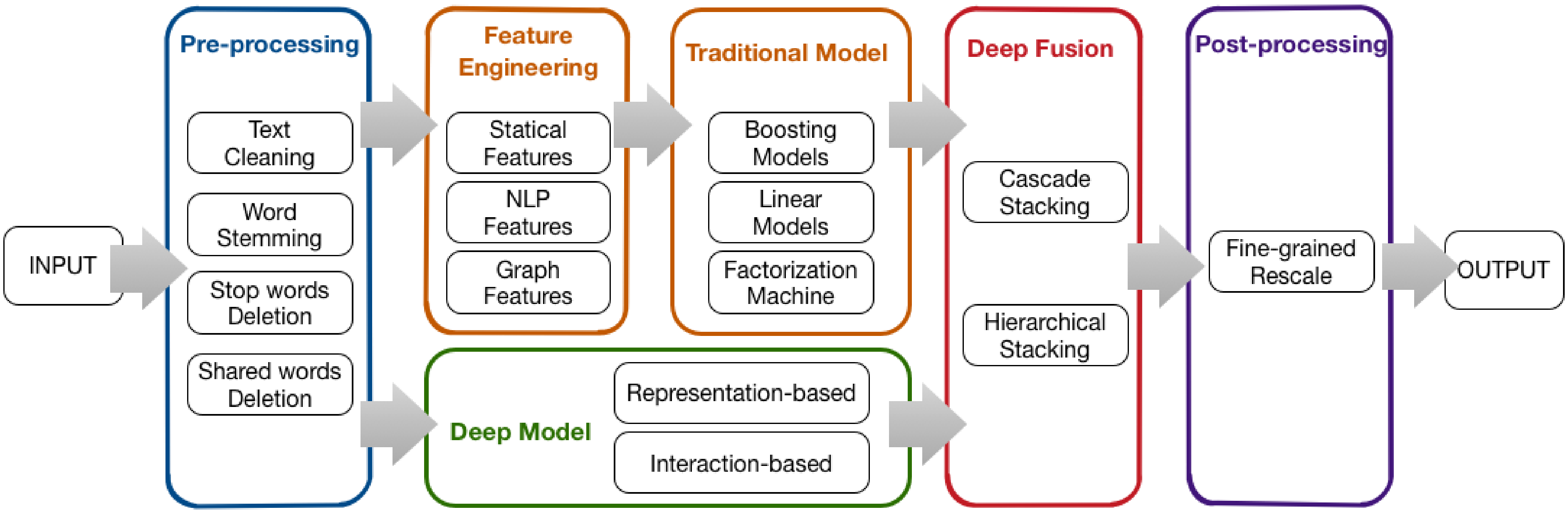
- Focus on text data, **Sparsity** and **Variance Length**.
- Support **JSON** config file to construct **DAG** networks.



Reference

- [1] https://www.kaggle.com/c/quora-question-pairs
- [2] https://github.com/pl8787/textnet-release
- [3] Pang L, Lan Y, Guo J, etal. Text Matching as Image Recognition[C]. Thirtieth AAAI Conference onArtificial Intelligence. 2016.
- [4] Wan S, Lan Y, Guo J, etal. A deep architecture for semantic matching with multiple positional sentencerepresentations[C]. Thirtieth AAAI Conference on Artificial Intelligence. 2016.
- [5] Wan S, Lan Y, Xu J, etal. Match-SRNN: Modeling the Recursive Matching Structure with Spatial RNN[C]. Twenty-FifthInternational Joint Conference on Artificial Intelligence (IJCAI-16). 2016.
- [6] https://github.com/HouJP/kaggle-quora-question-pairs
- [7] https://github.com/pl8787/textnet-release

Conclusion



INPUT
Pre-processing
Text Cleaning
Word Stemming
Stop words Deletion
Shared words Deletion
Feature Engineering
Statical Features
NLP Features
Graph Features
Traditional Model
Boosting Models
Linear Models
Factorization Machine
Deep Model
Representation-based
Interaction-based
Deep Fusion
Cascade Stacking
Hierarchical Stacking
Post-processing
Fine-grained Rescale
OUTPUT

Thanks!

Q & A