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?"

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

3307

Kaggle Rankings

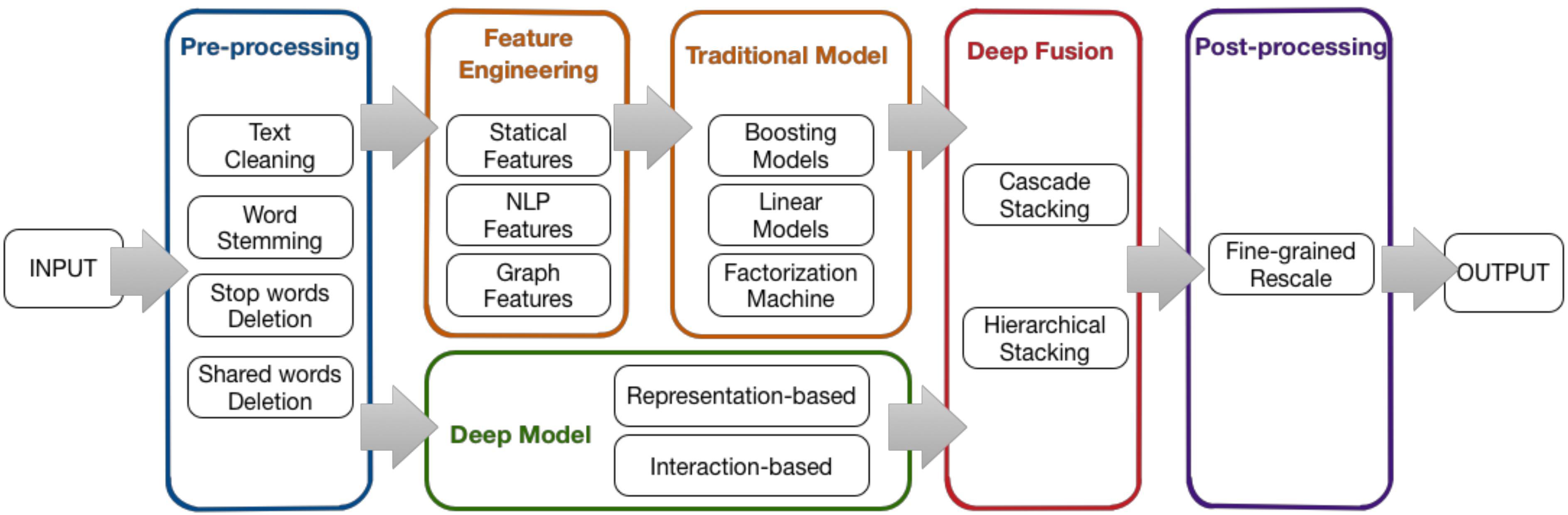
1	Gilberto Titericz Junior
2	Stanislav Semenov
3	Μαριος Μιχαηλιδης KazAnova
4	Faron
5	idle_speculation
6	Eureka
7	Silogram
8	Little Boat
9	utility
10	raddar

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

The framework of our solution:



Content

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

Preprocessing

Made some different versions of original data:

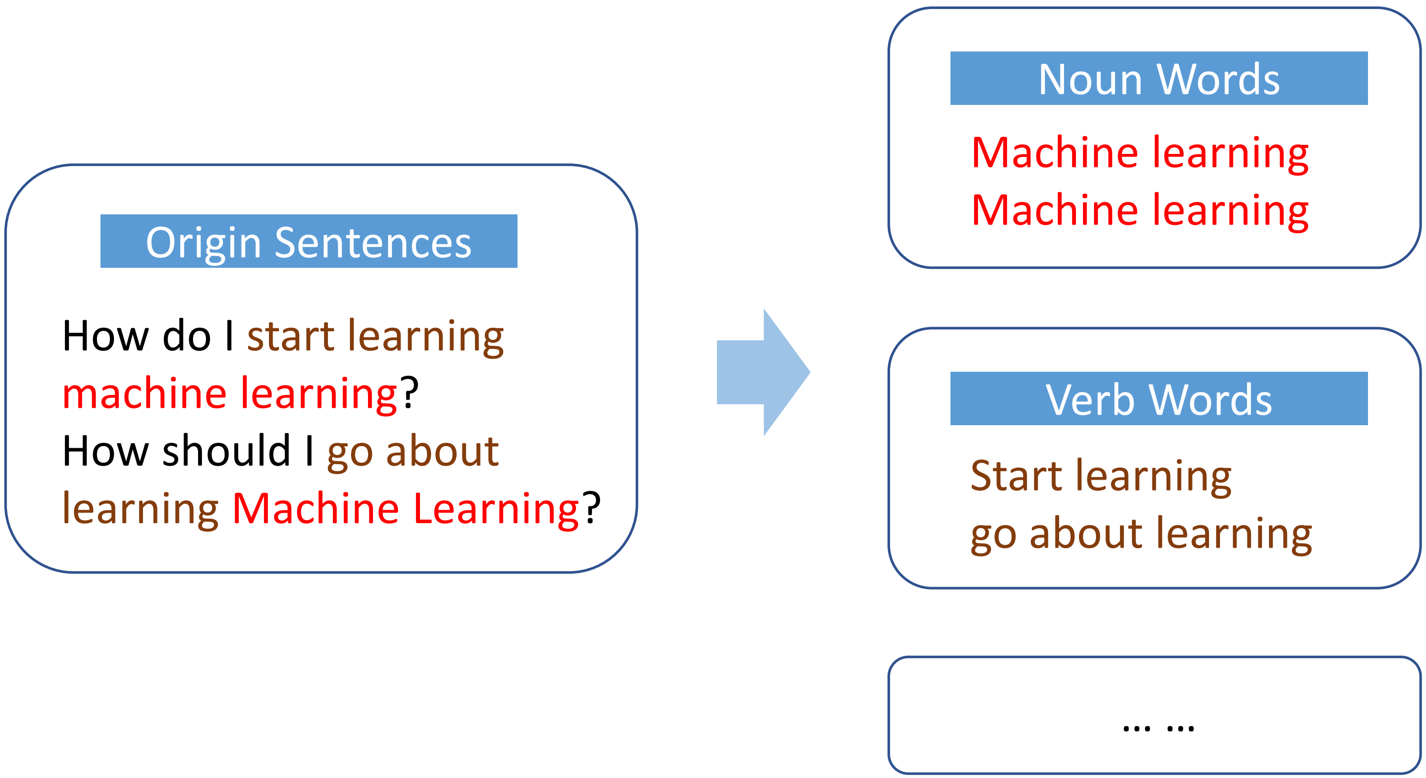
- Lower case
- Text cleaning
- Stop words removal
- Word stemming
- Punctuation Cleaning
- Shared words deletion
- Part of Speech Group

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.



Content

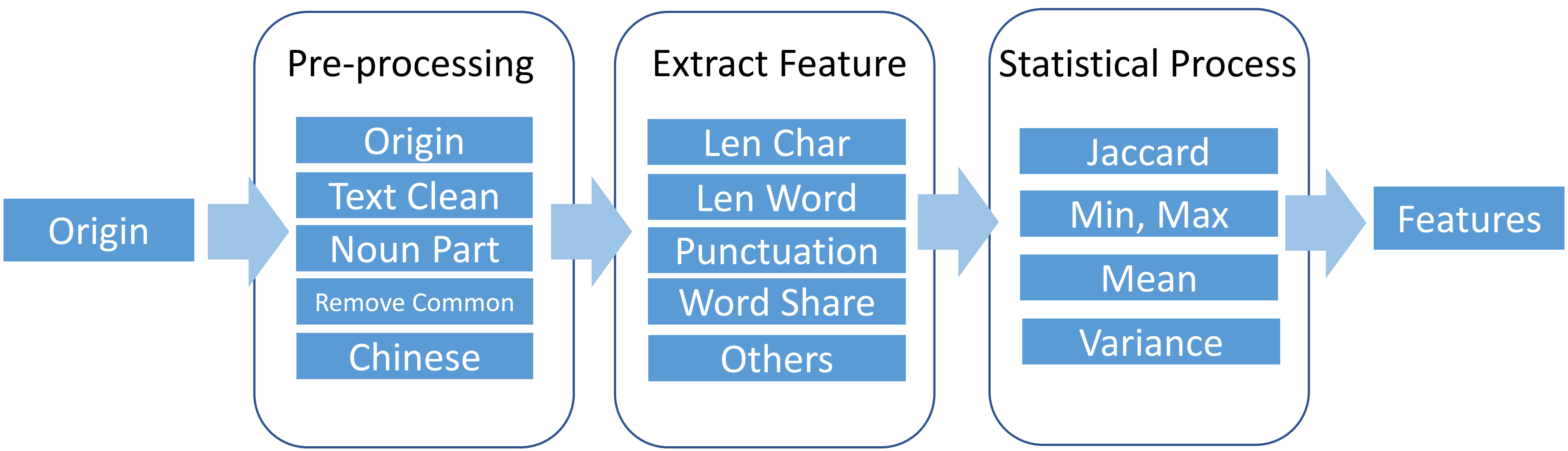
- Introduction
- Solution
  - Pre-processing
  - **Feature-Engineering**
  - Deep Model
  - Traditional Model
  - Stacking
  - Post-processing
- Conclusion

Feature Engineering

- 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

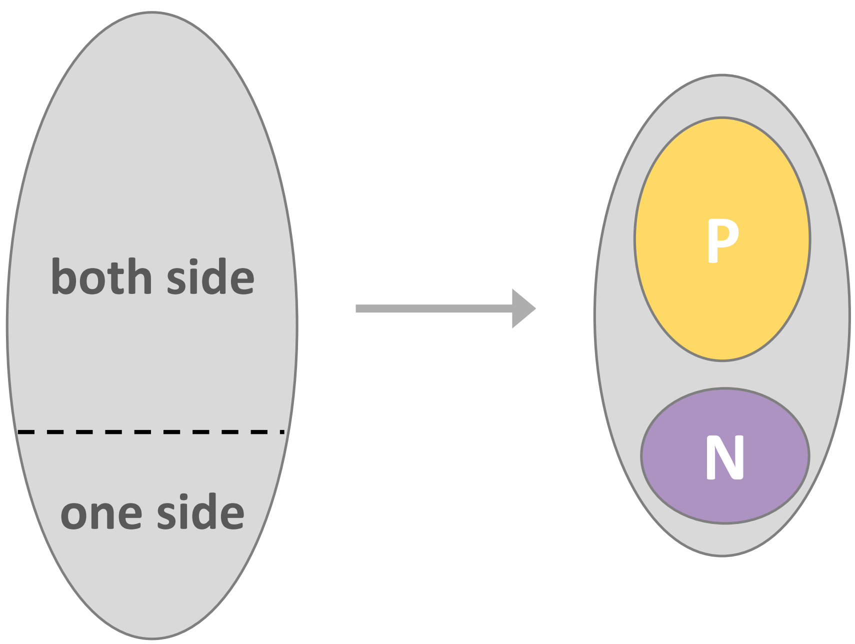
Statistical Features

- 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

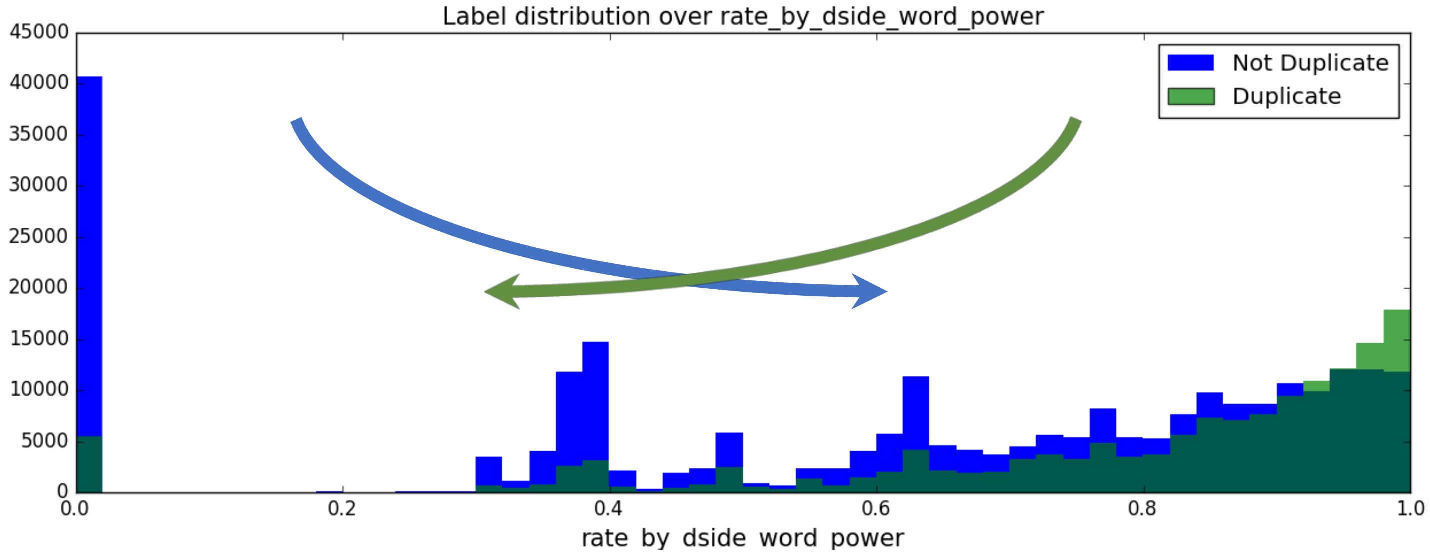
both side data set
contained specified word

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

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

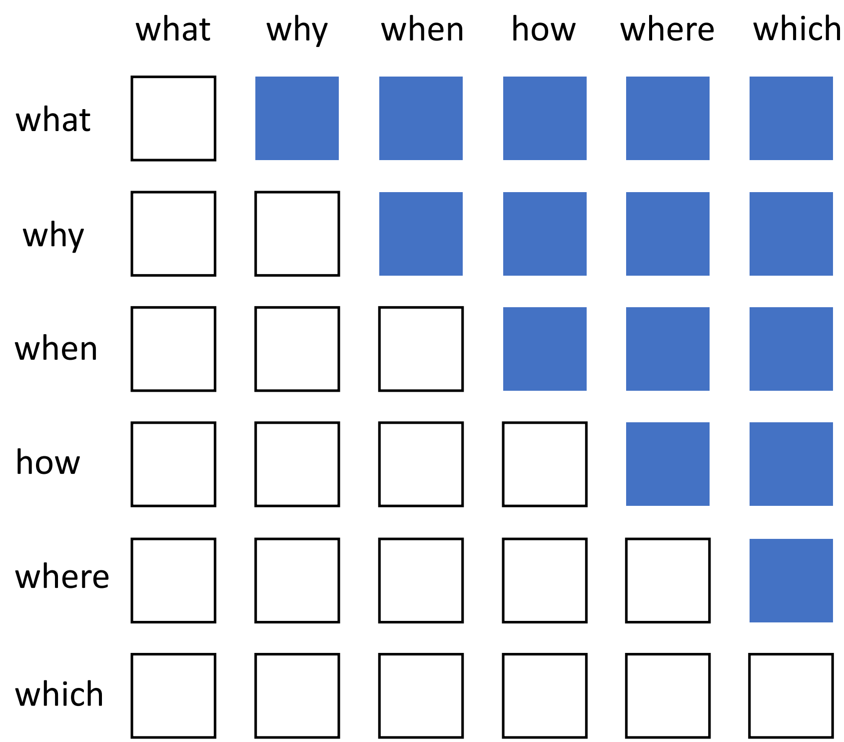
Statistical Features • **Powerful Words**

- Words which make two sentences express same meaning.



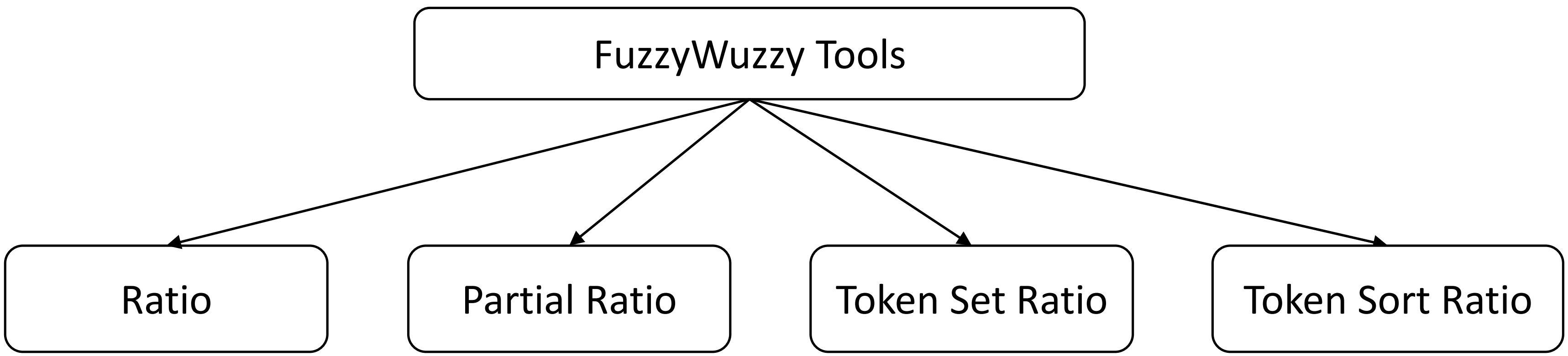
Statistical Features • **Interrogative Words**

- Build a coexistence matrix for interrogative words.



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

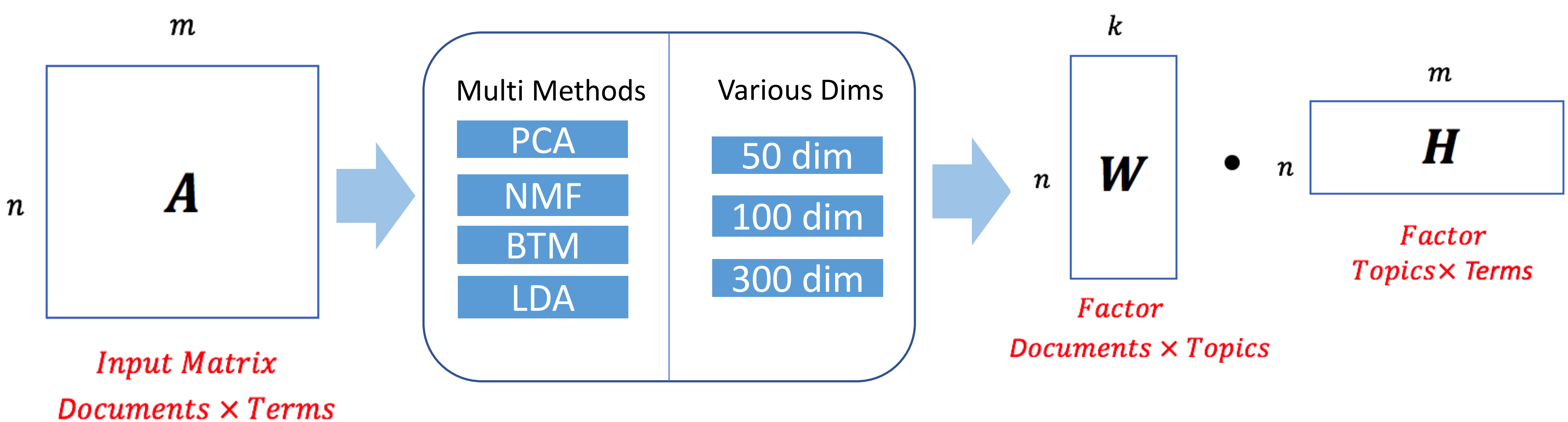
Ratio:88
Partial_ratio:88
Token_set_ratio:80
Token_sort_ratio:87

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

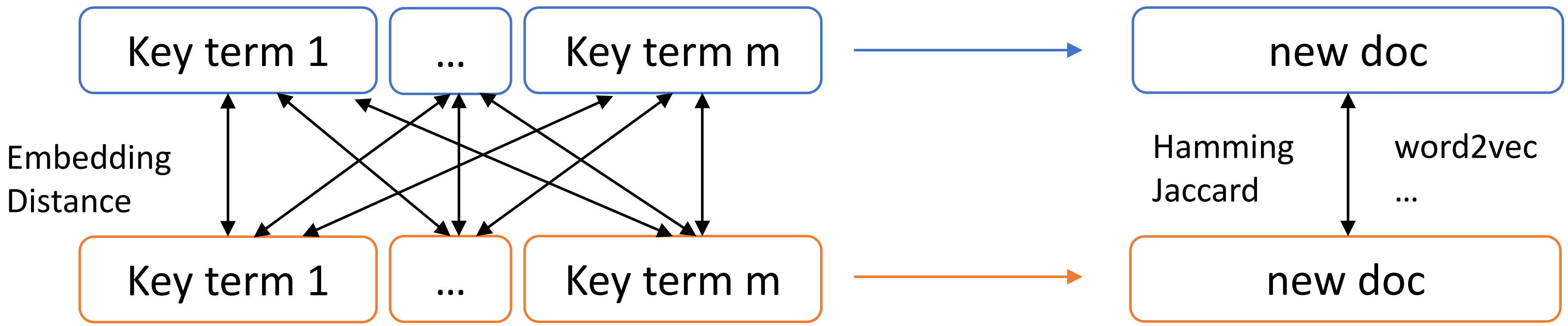
Topic Model Features

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



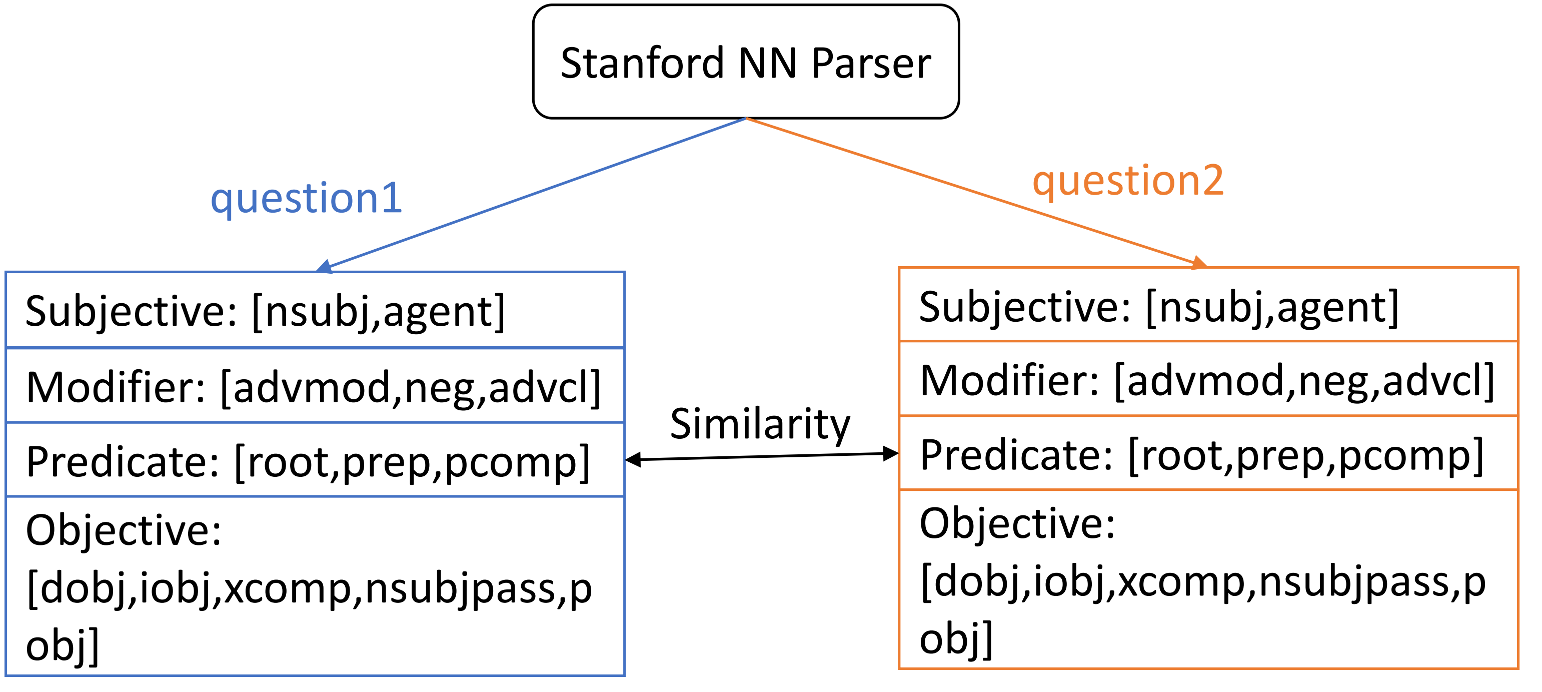
Key Phrase Extraction

- 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

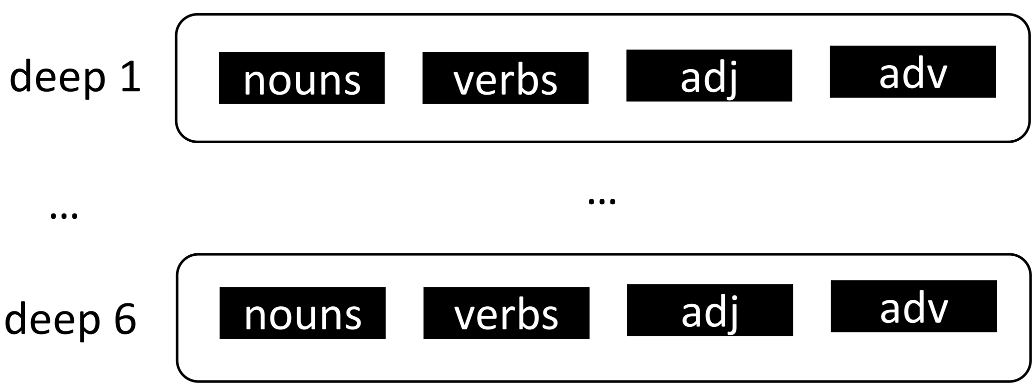
- Sentence principal component extraction
- Light rules can be summed up based on Dep-Parser

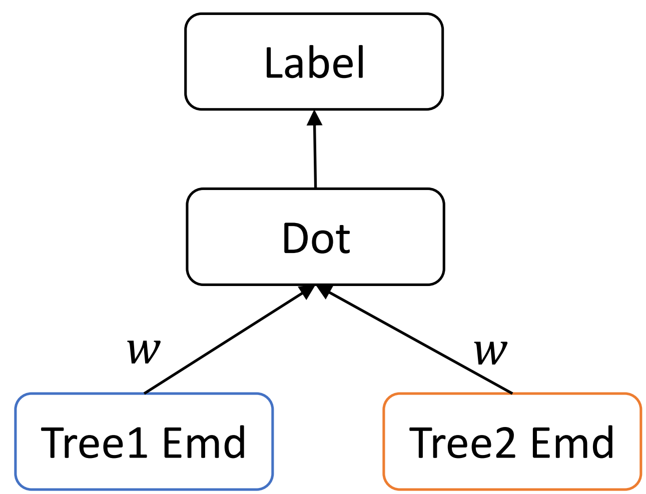


Dependency Parsing

- 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

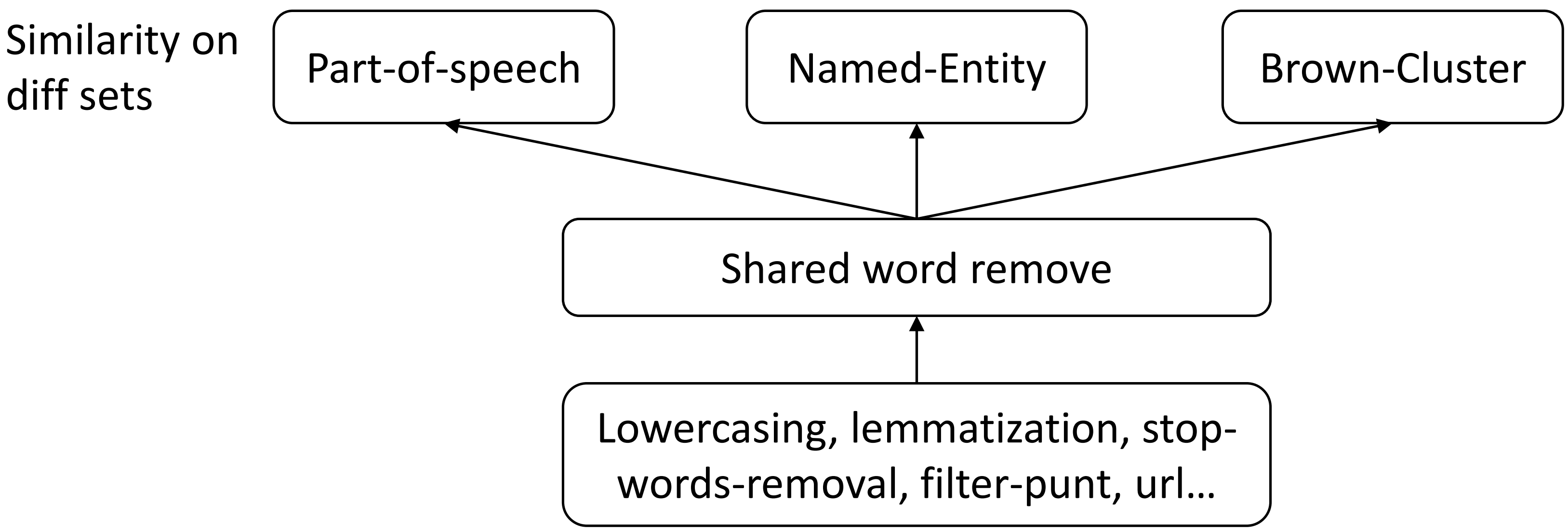
$$TreeEmd = \sum_{i=1}^{6}\sum_{j=1}^{4} PosEmd_{i,j} * w_{i,j}$$





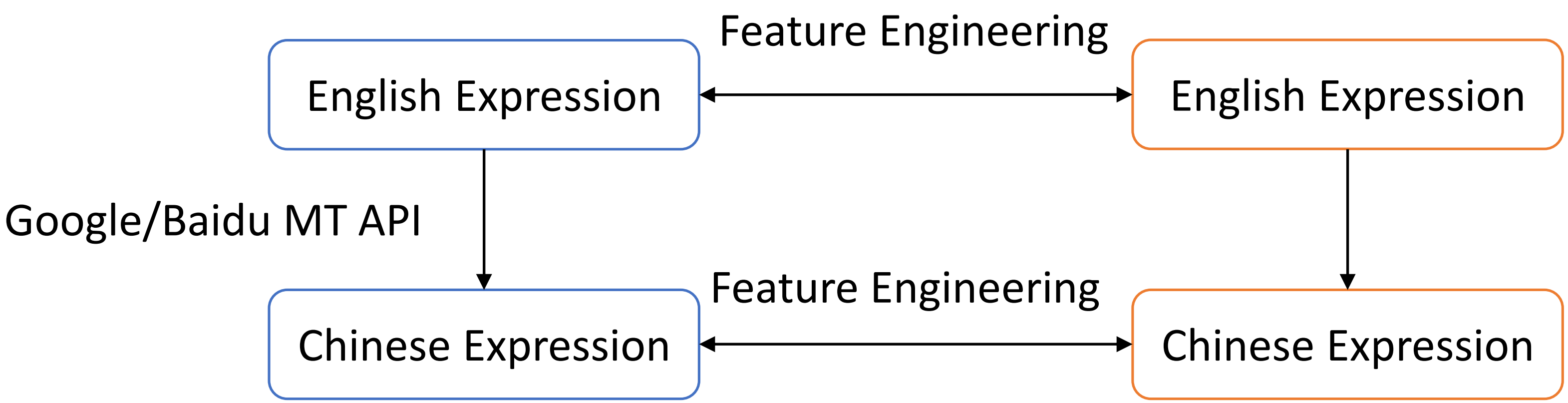
Differential Analysis

- 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)

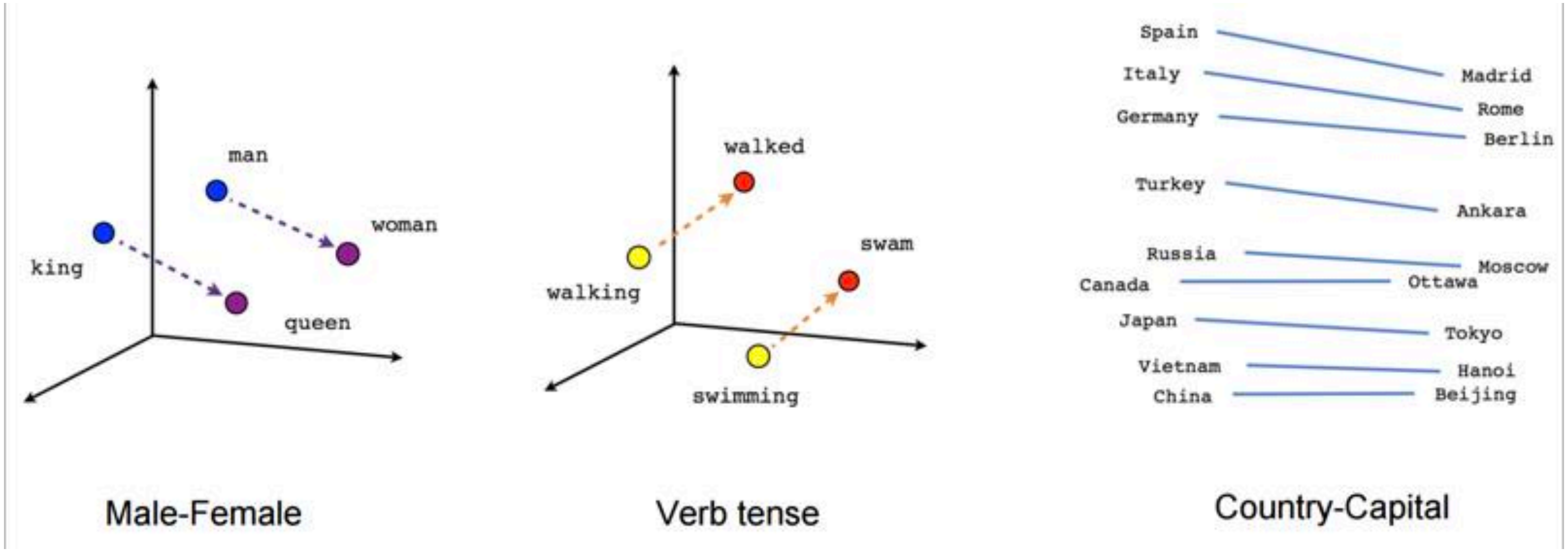
- Translate English to Chinese or other languages
- Same feature engineering repeat on translated languages
- Machine Translation are better on Polysemy and Unification



Representation Features

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

Word Representation



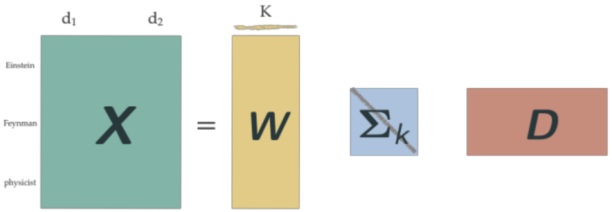
vector[Queen] = vector[King] - vector[Man] + vector[Woman]

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

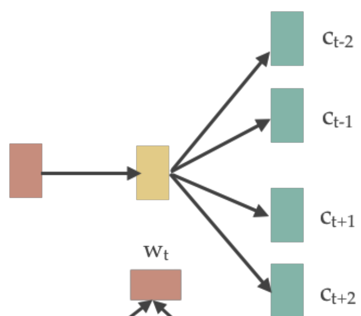
Word Representation

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.

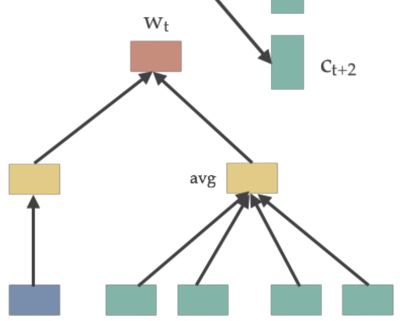
- LSI: SVD decomposition of **Word-Document** Co-occurrence Matrix



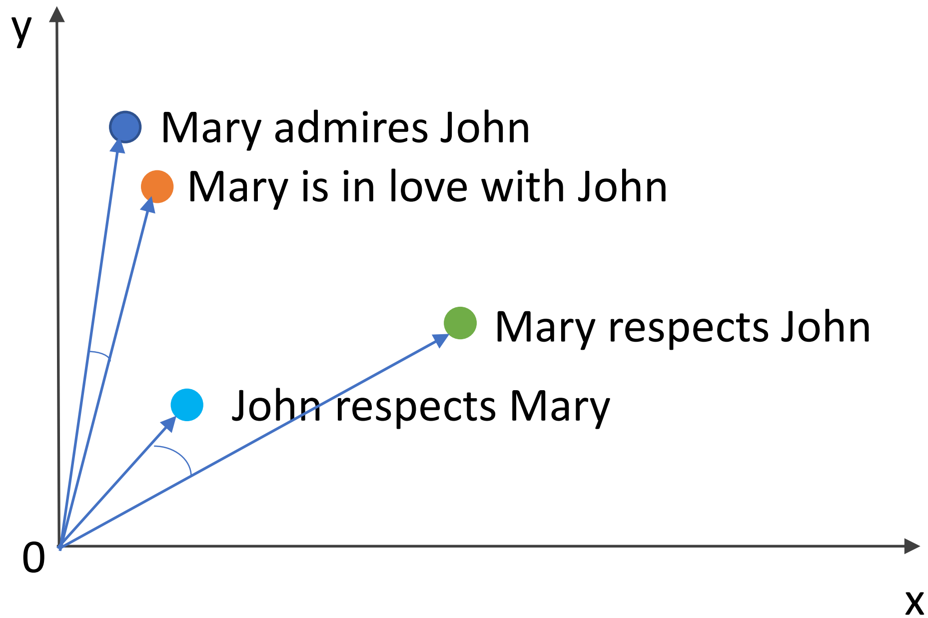
- Word2vec: word predict **local context** words.



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



Sentence Representation

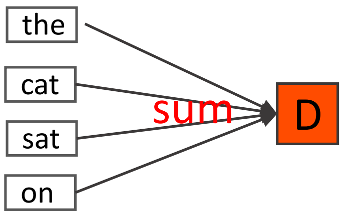


- Semantically similar sentence are mapped to nearby points
- Fluent & efficient representation:
    - Continuous vector space
    - Map varied-length sentence to fix-length vectors

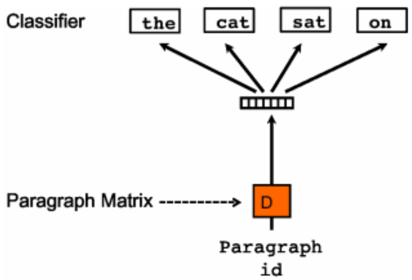
Sentence Representation

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

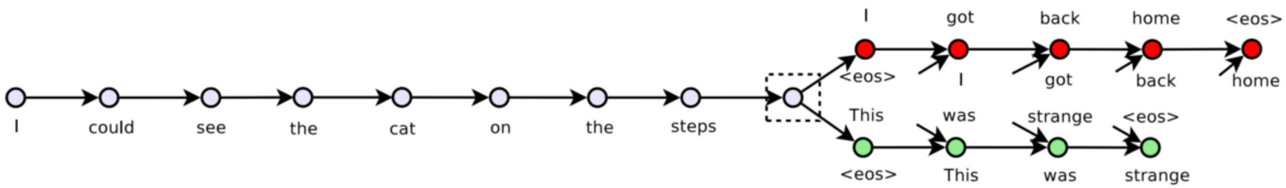
- Weighted Sum of Word Embeddings



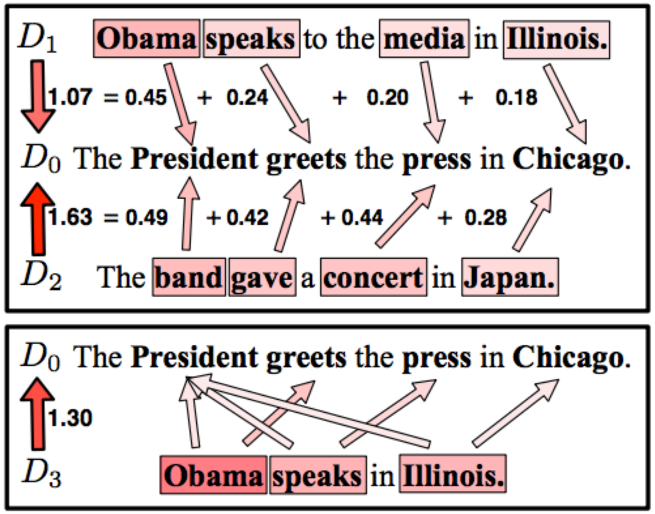
- Paragraph Vector



- 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)

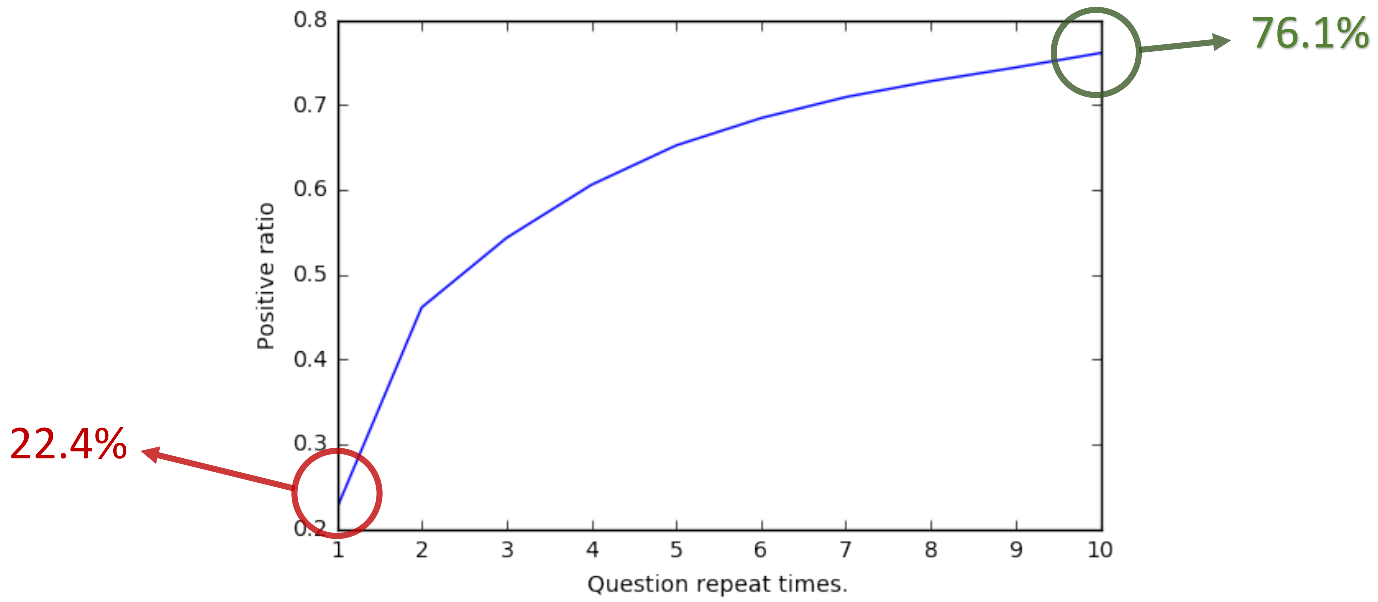
Build Graph

- 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.

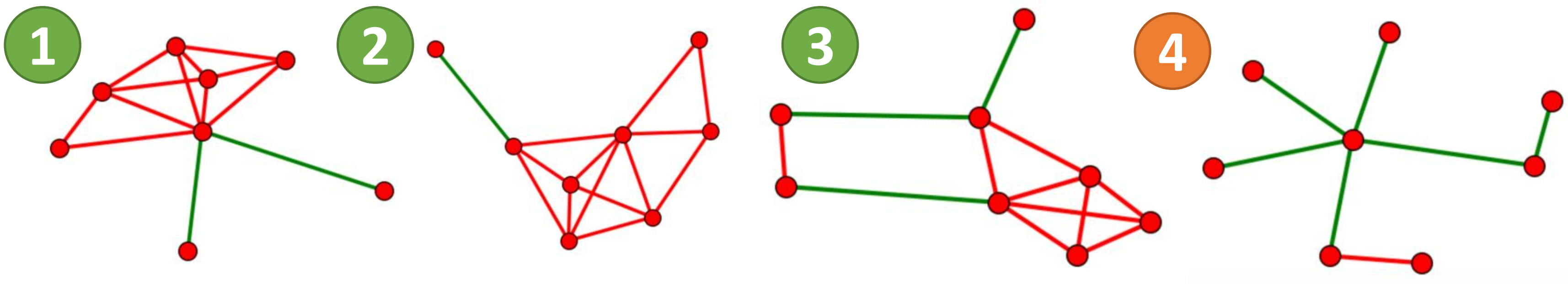


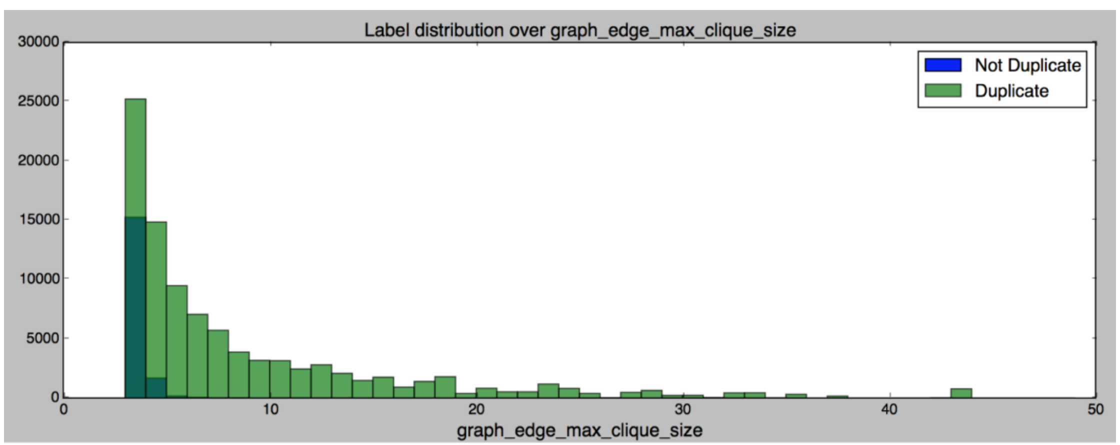
Explanation:

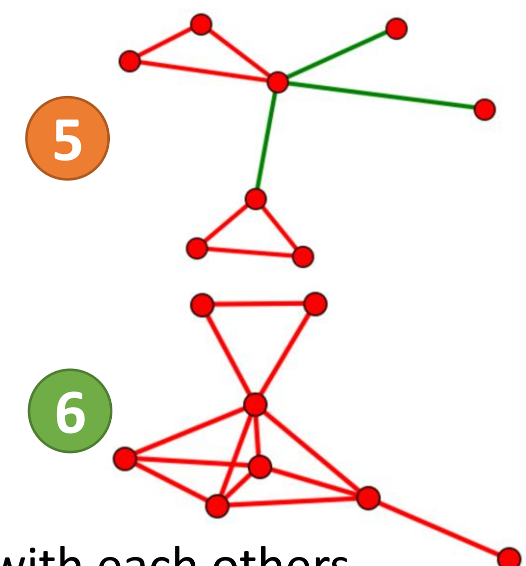
Frequent viewed questions = Hot topics = High duplicate ratio

Structure information

- Component & Clique analysis



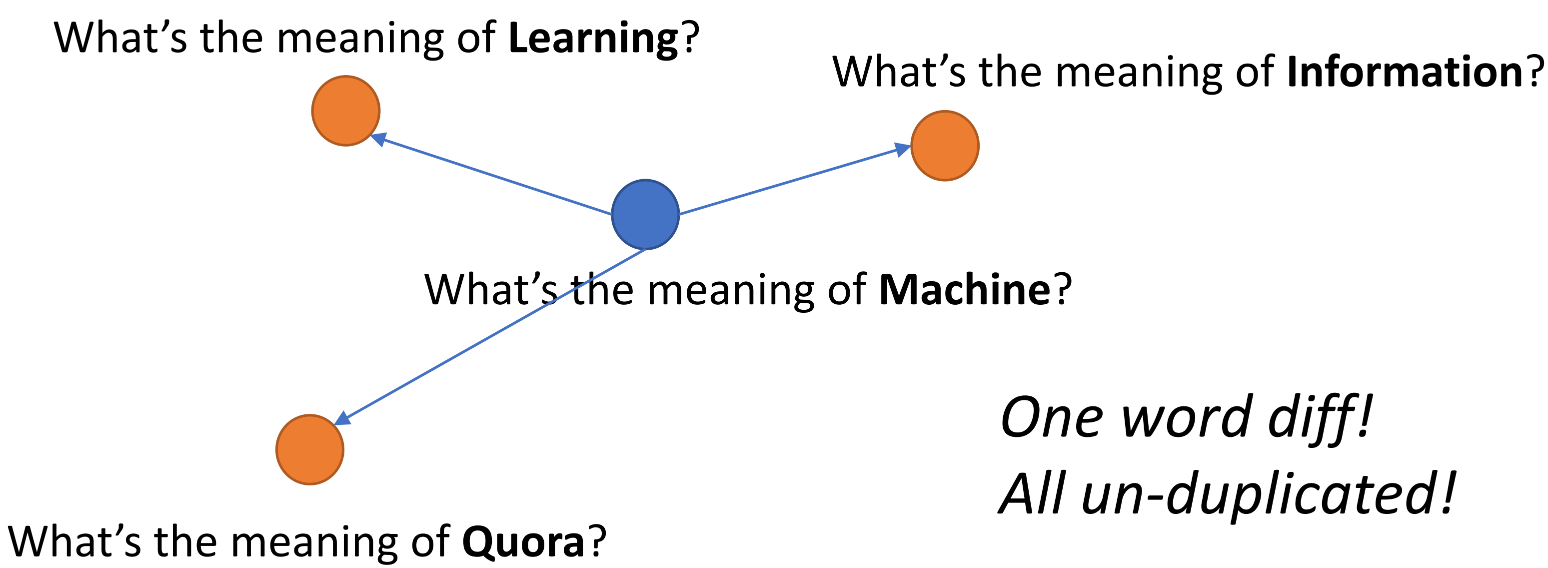




Explanation:
Different descriptions of the same question **link tightly** with each others.

Propagation Information

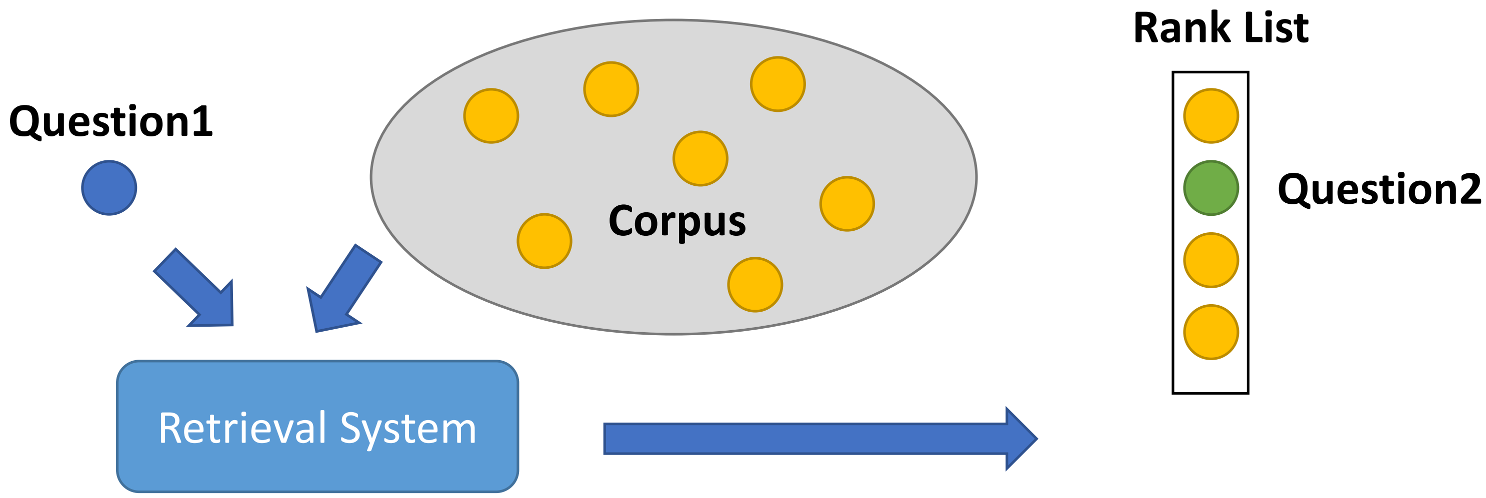
- Neighbor Analysis
  - In Co-occurrence Based Graph, neighbors' features can be used to represent current question.
  - Such as word shared count



One word diff!
All un-duplicated!

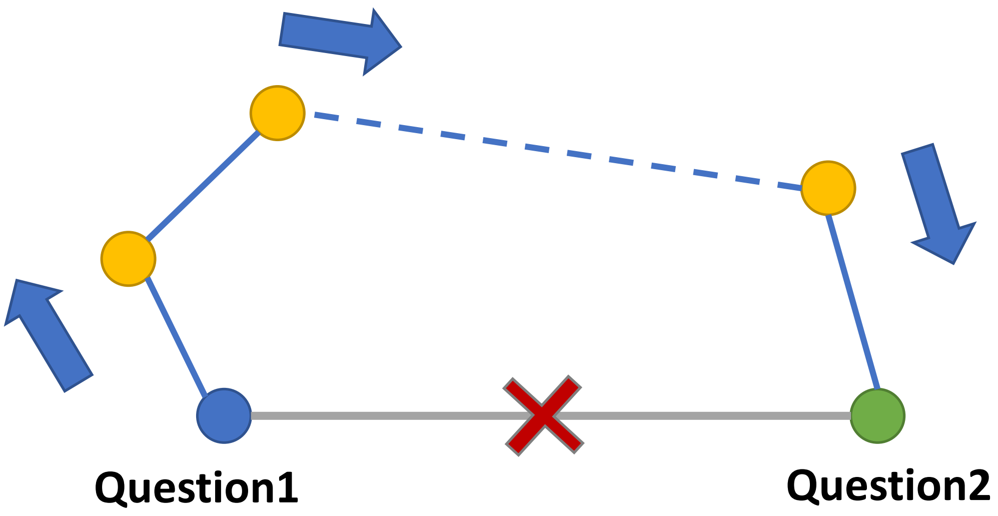
Propagation Information

- 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.



Content

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

Deep Models

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

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

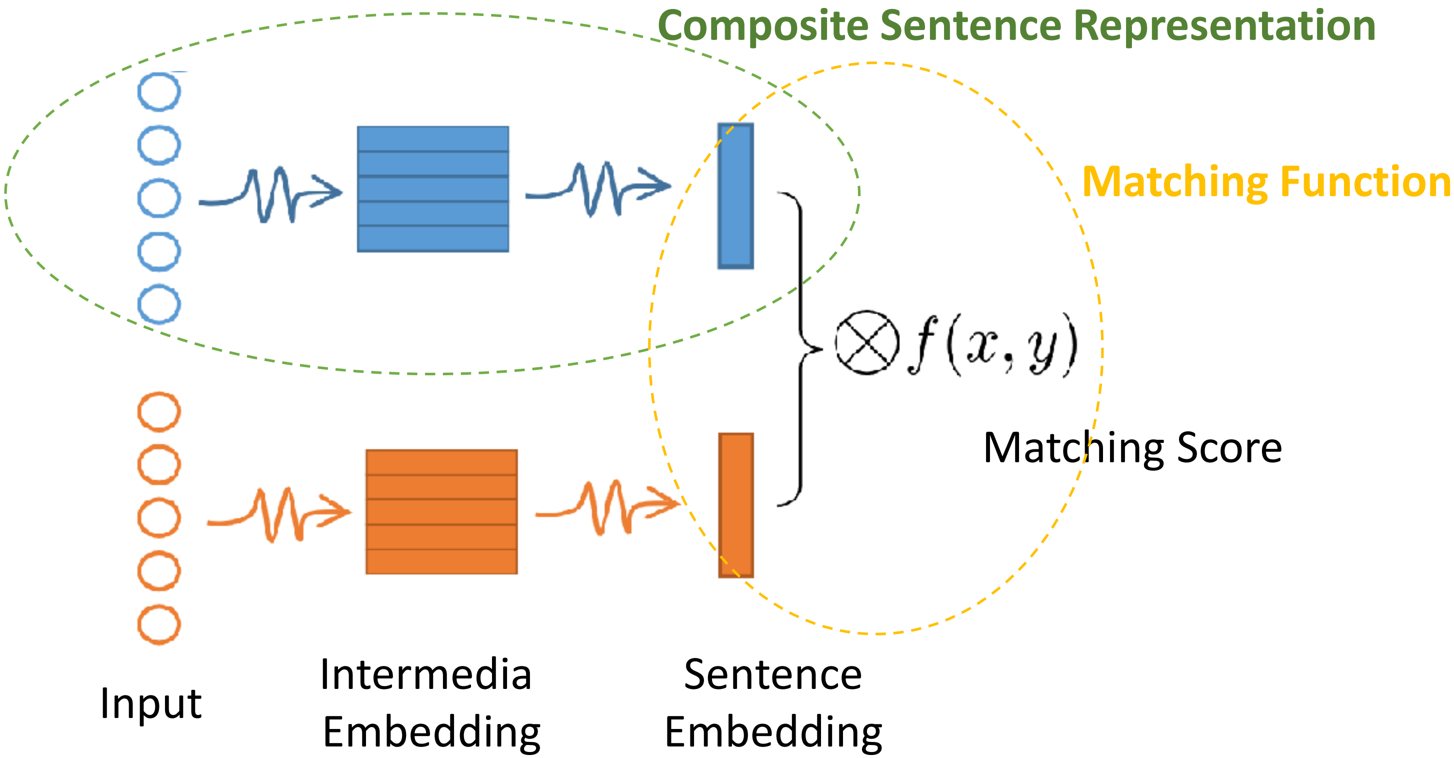
Scoring function based on the interaction between texts

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

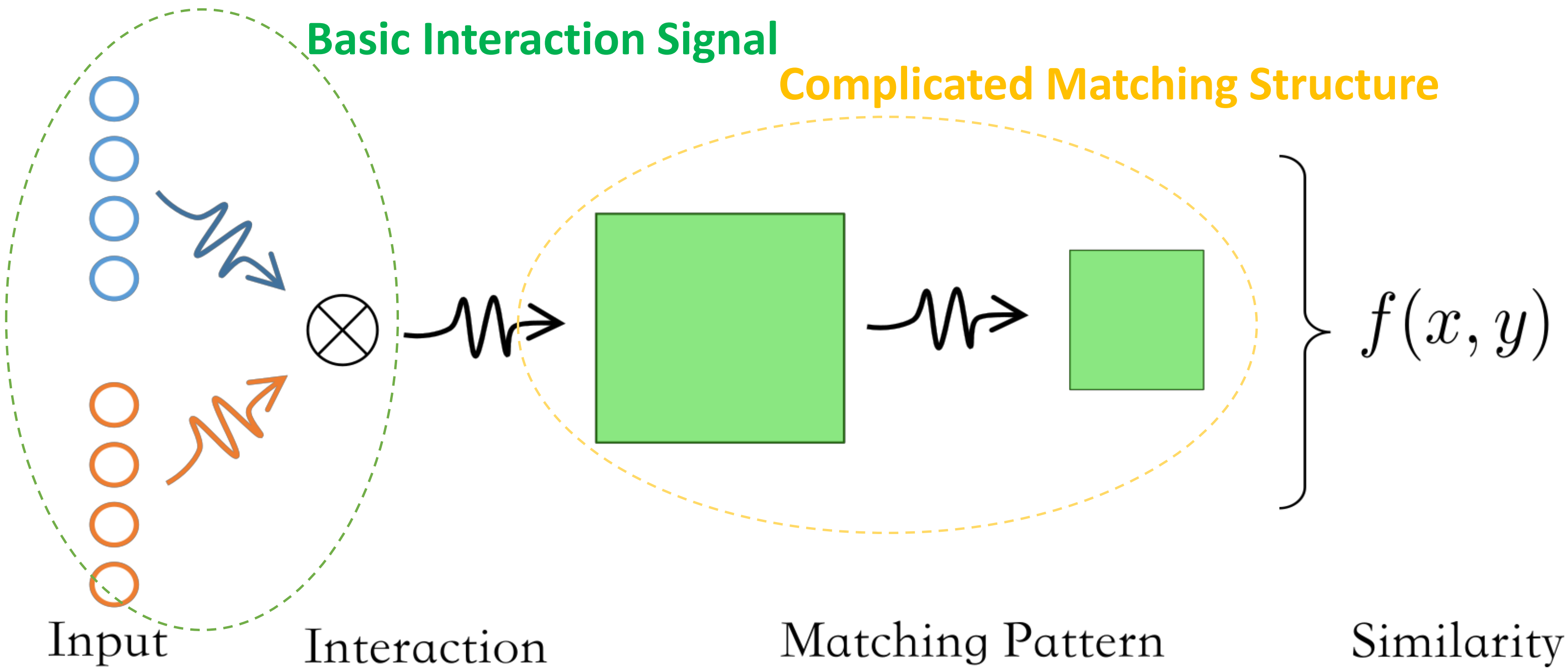


Typical Representation Based Models

- 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

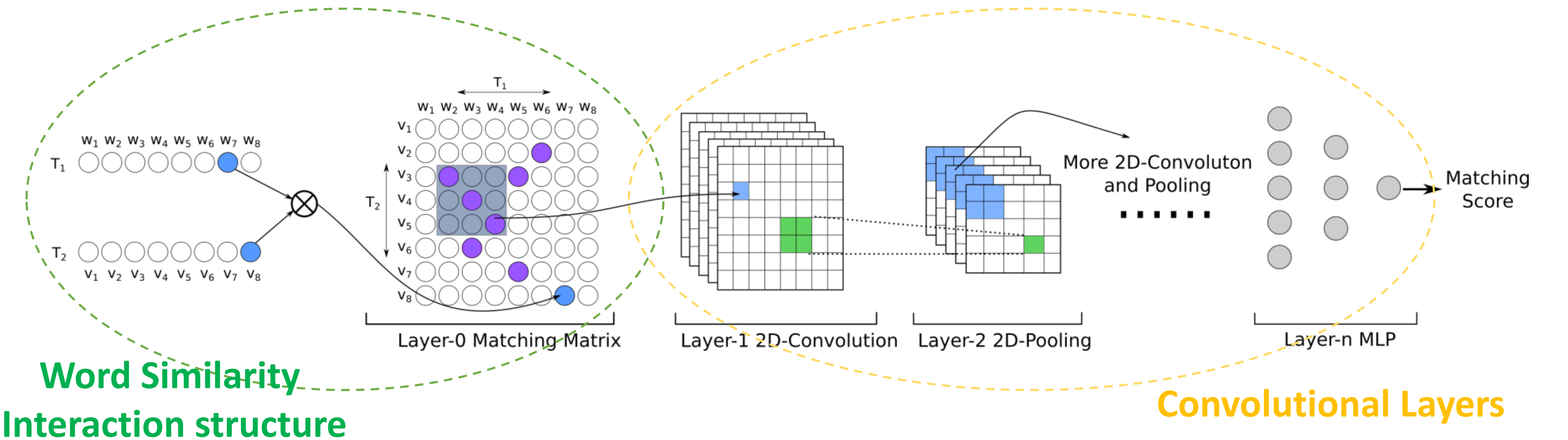


Typical Interaction Based Methods

- 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)

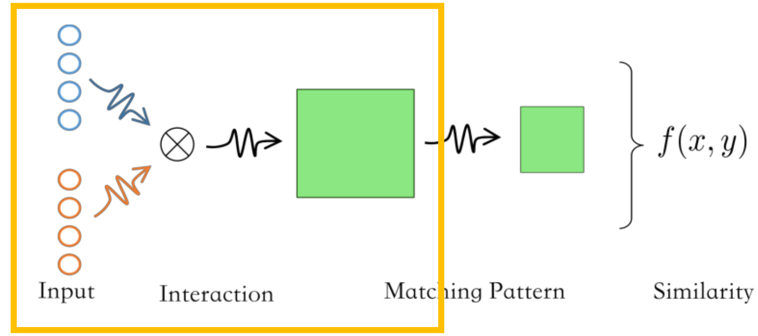
MatchPyramid

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



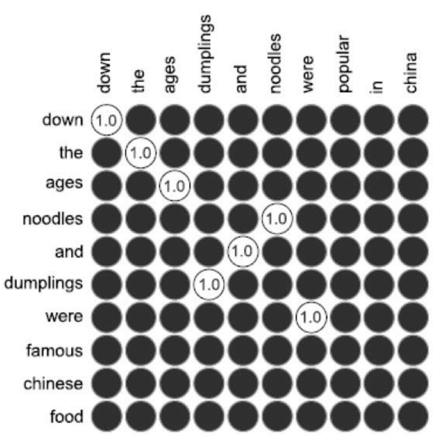
Pang L, Lan Y, Guo J, et al. Text matching as image recognition//Proceedings of the 30th AAAI Conference on Artificial Intelligence. Phoenix, USA, 2016: 2793-2799.

MatchPyramid
- Matching Matrix

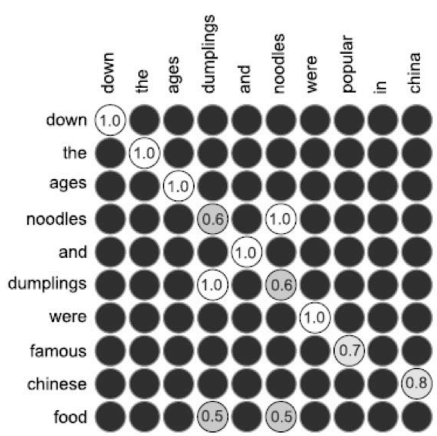


- Bridging the Gap between Text Matching and Image Recognition.

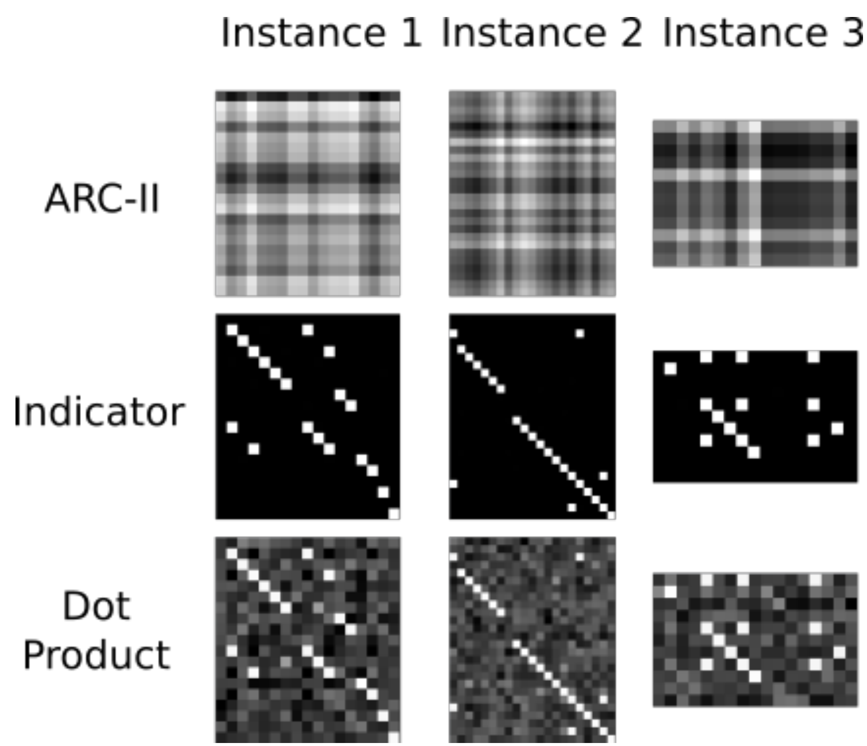
$$\mathbf{M}_{ij} = w_i \otimes v_j$$



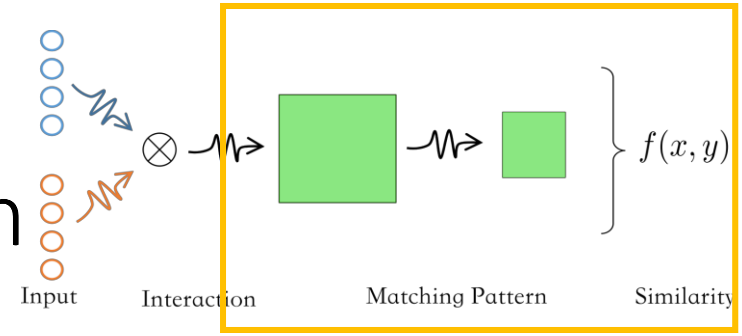
(a) Matching Matrix-Indicator



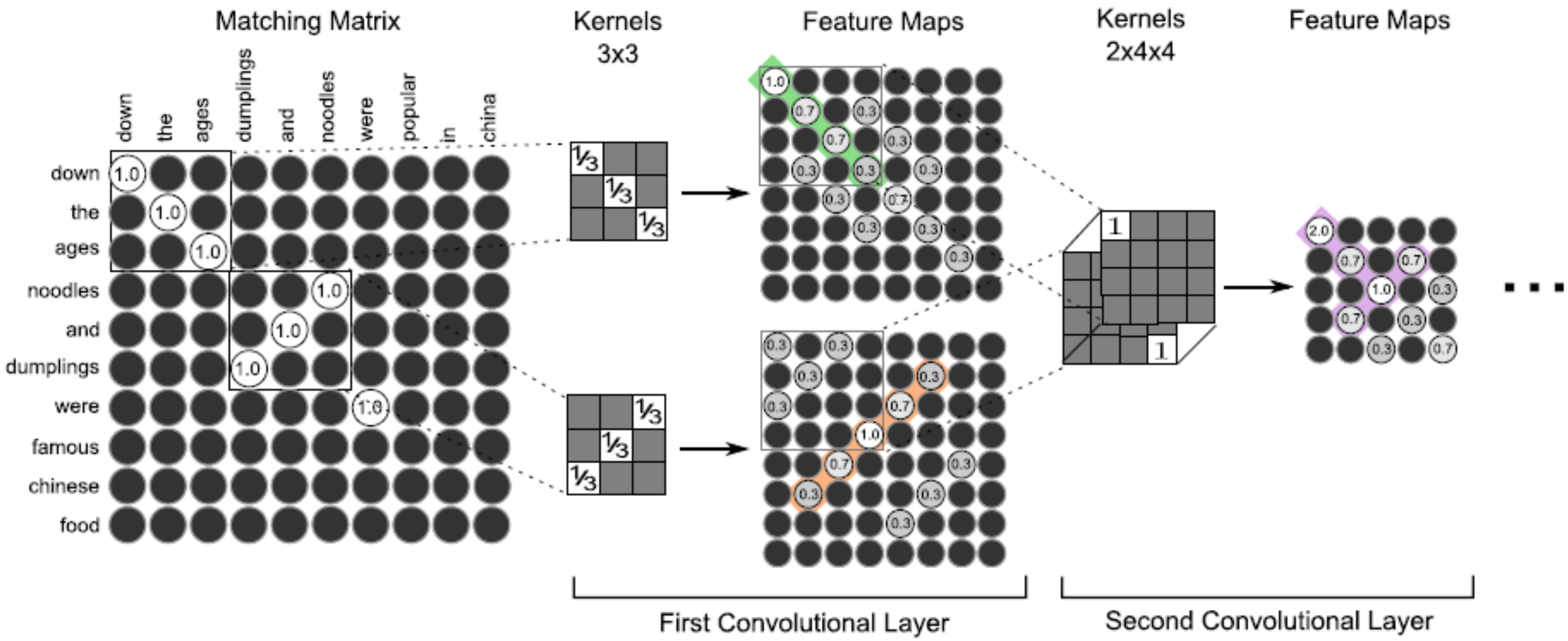
(b) Matching Matrix-Cosine



MatchPyramid
- Hierarchical Convolution

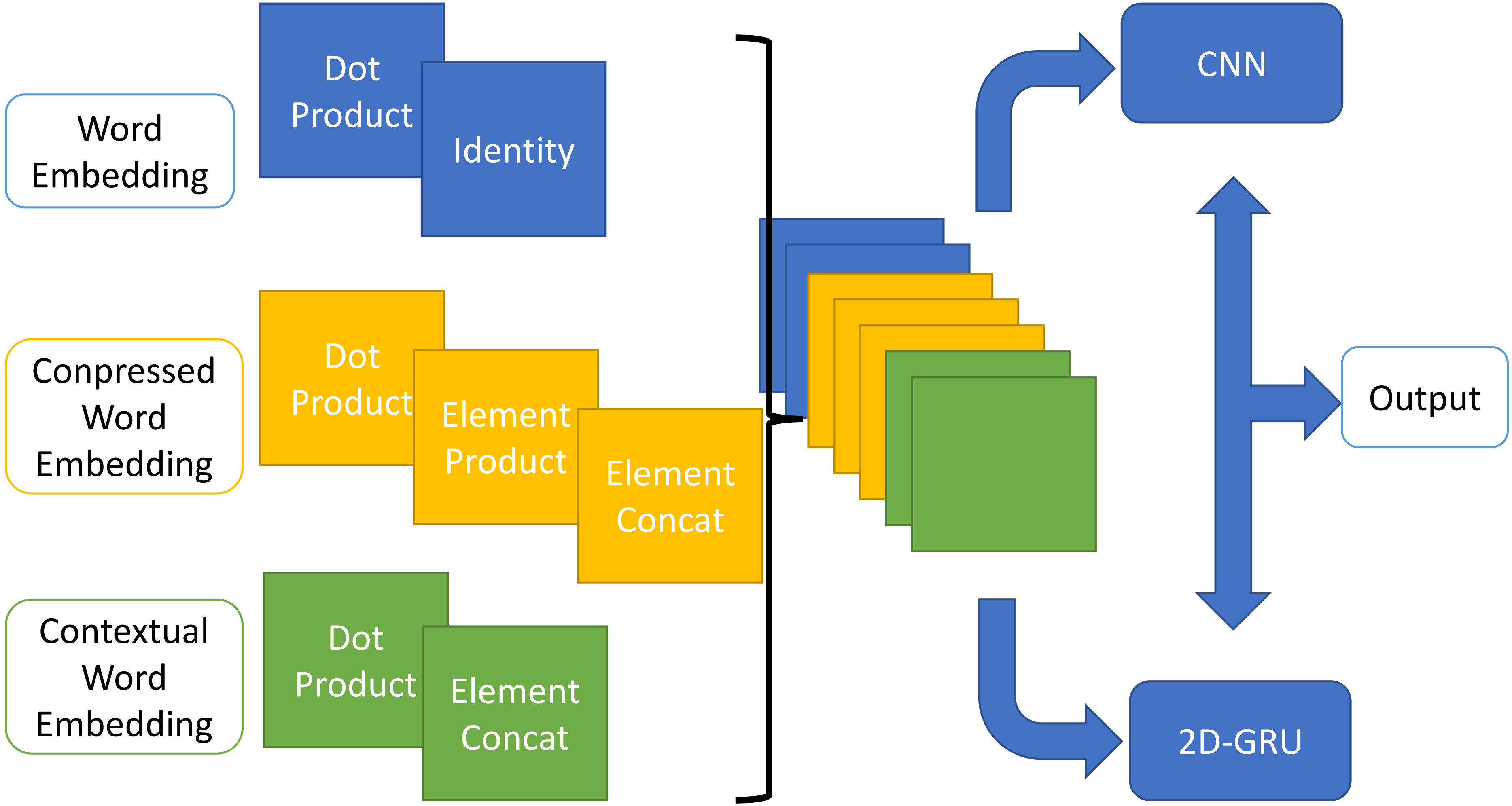


- A way to capture rich matching patterns

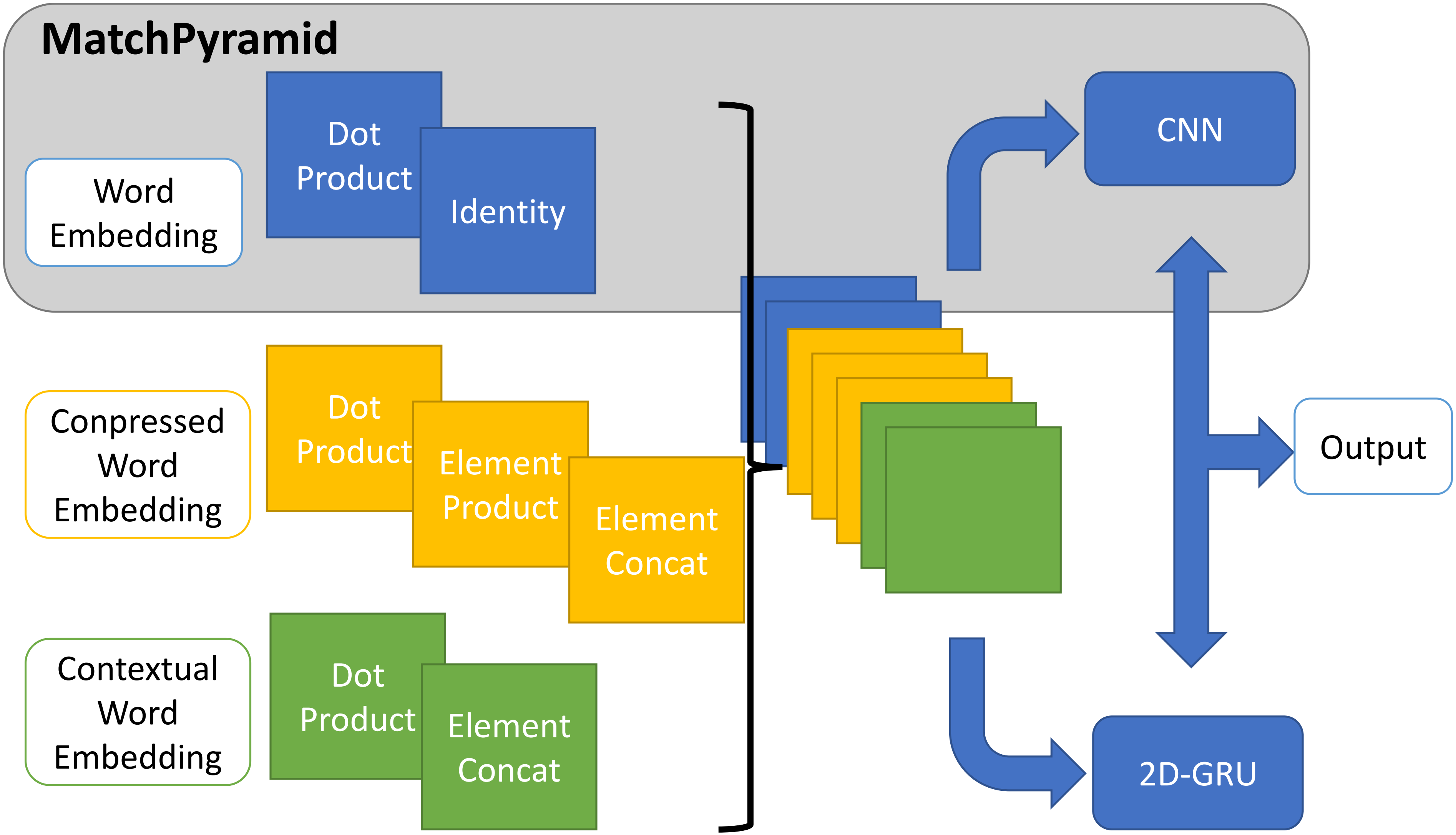


Best Single Deep Model

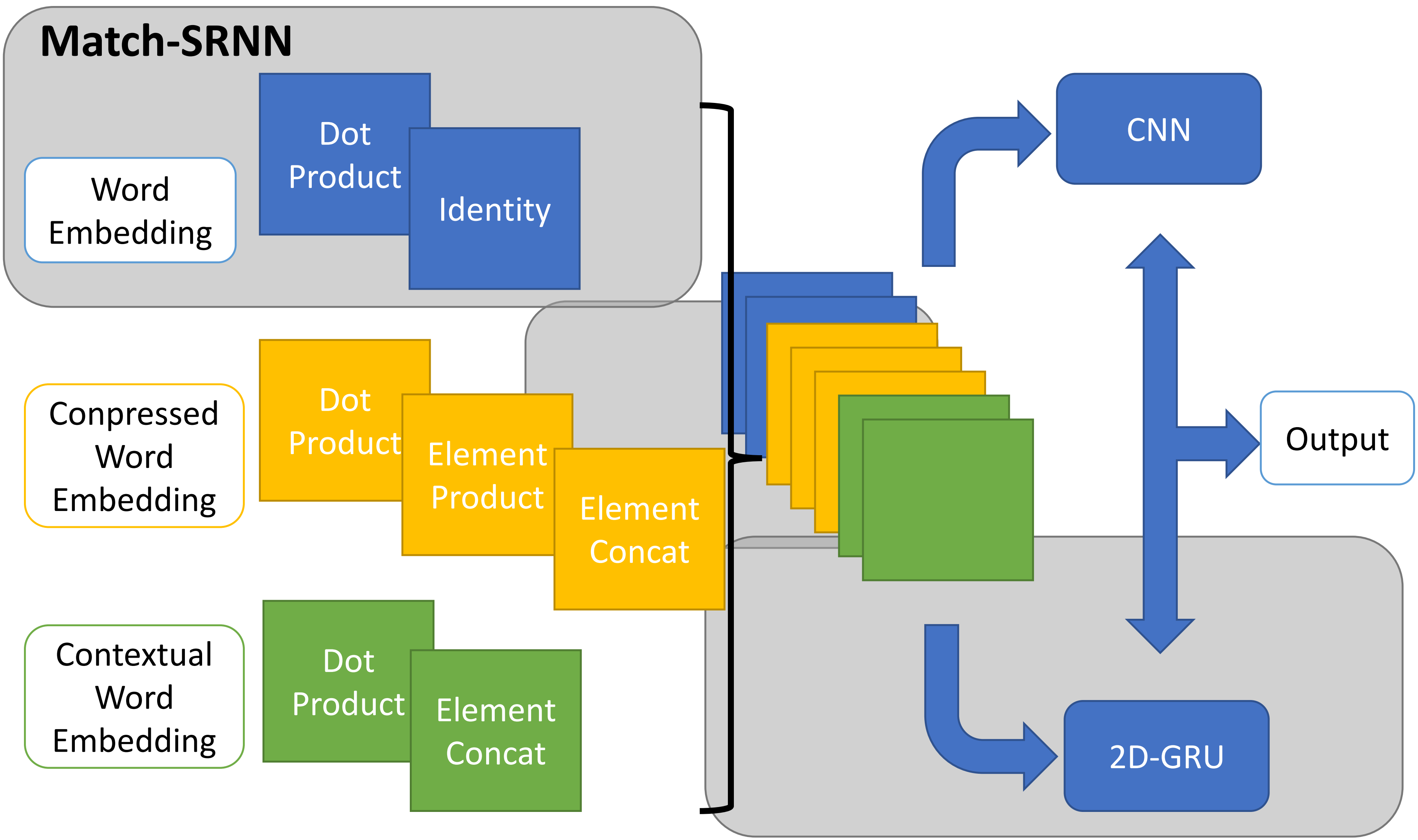
Combine of MatchPyramid, Match-SRNN and MVLSTM.



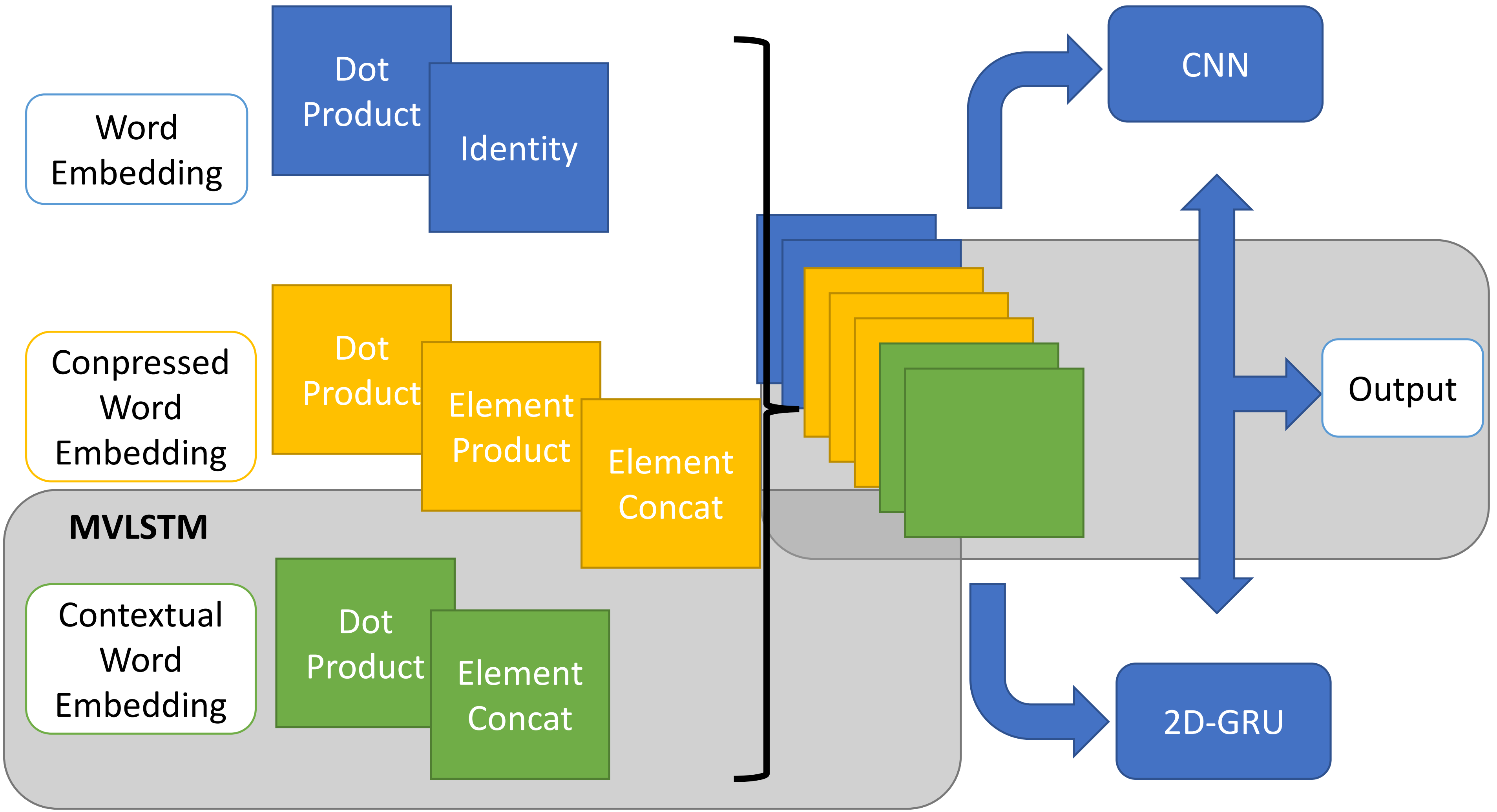
Best Single Deep Model



Best Single Deep Model



Best Single Deep Model

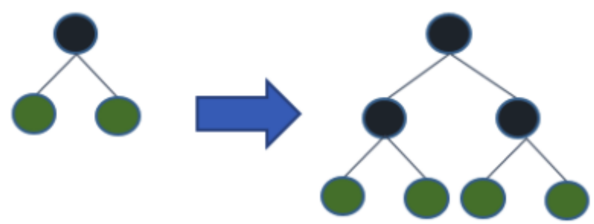


Content

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

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

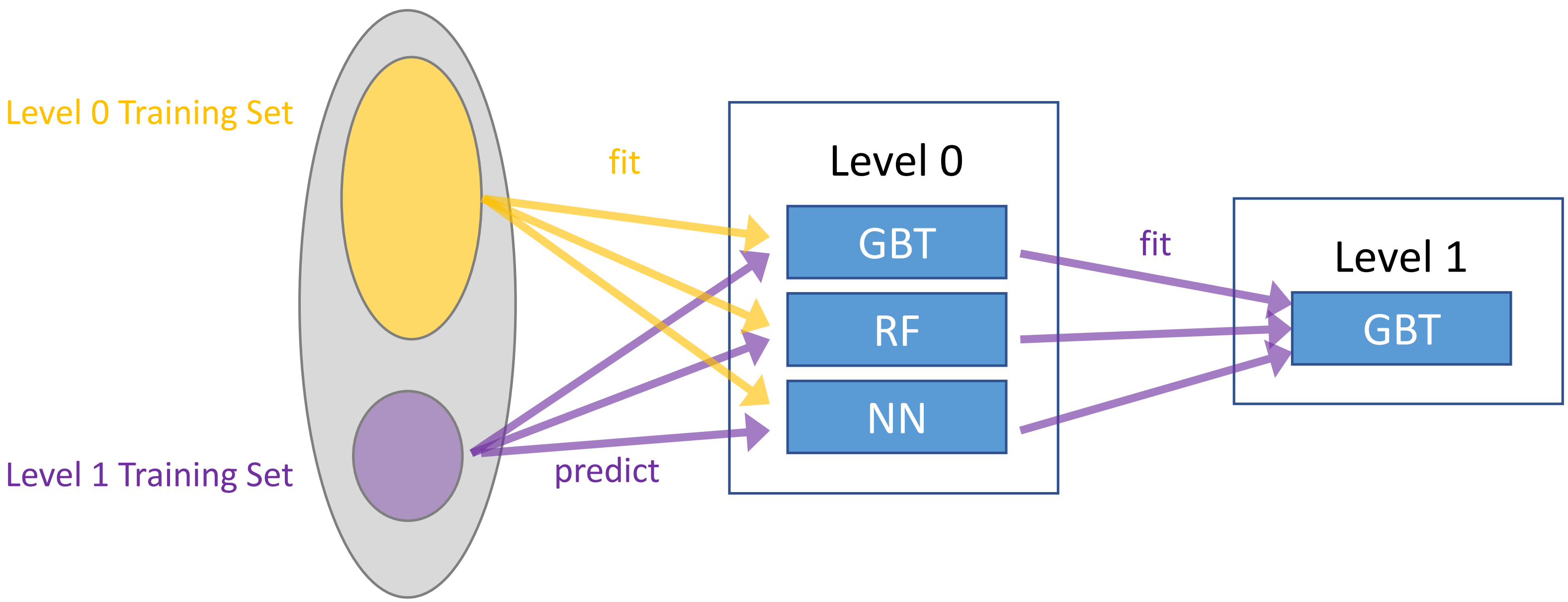
- Extract Linear and Second order interaction extra info
- Apply to 1.5 million sparse features
- Sensitive to feature scale, must normalization or hash bin.

Content

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

Traditional Stacking

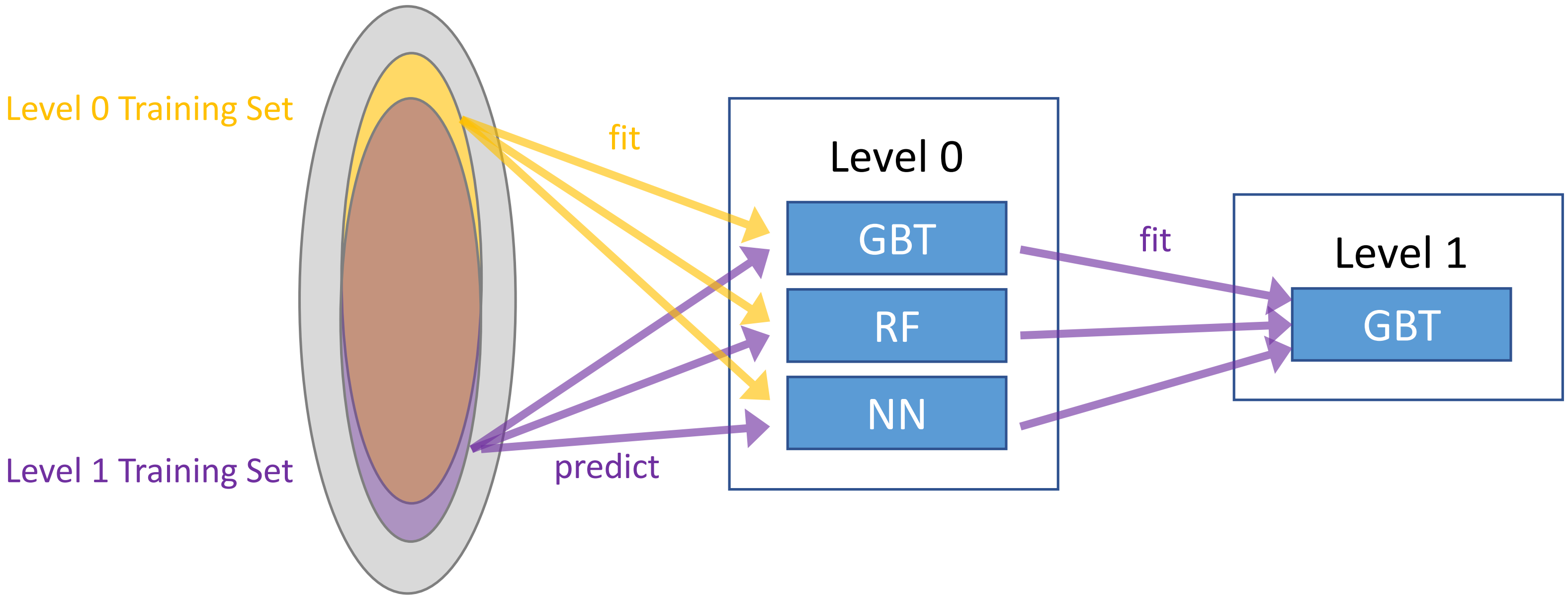
- Split the training set into two **disjoint** sets.
- **Train** several base learners on the first part and **Test** the base learners on the second part.



Deep Fusion

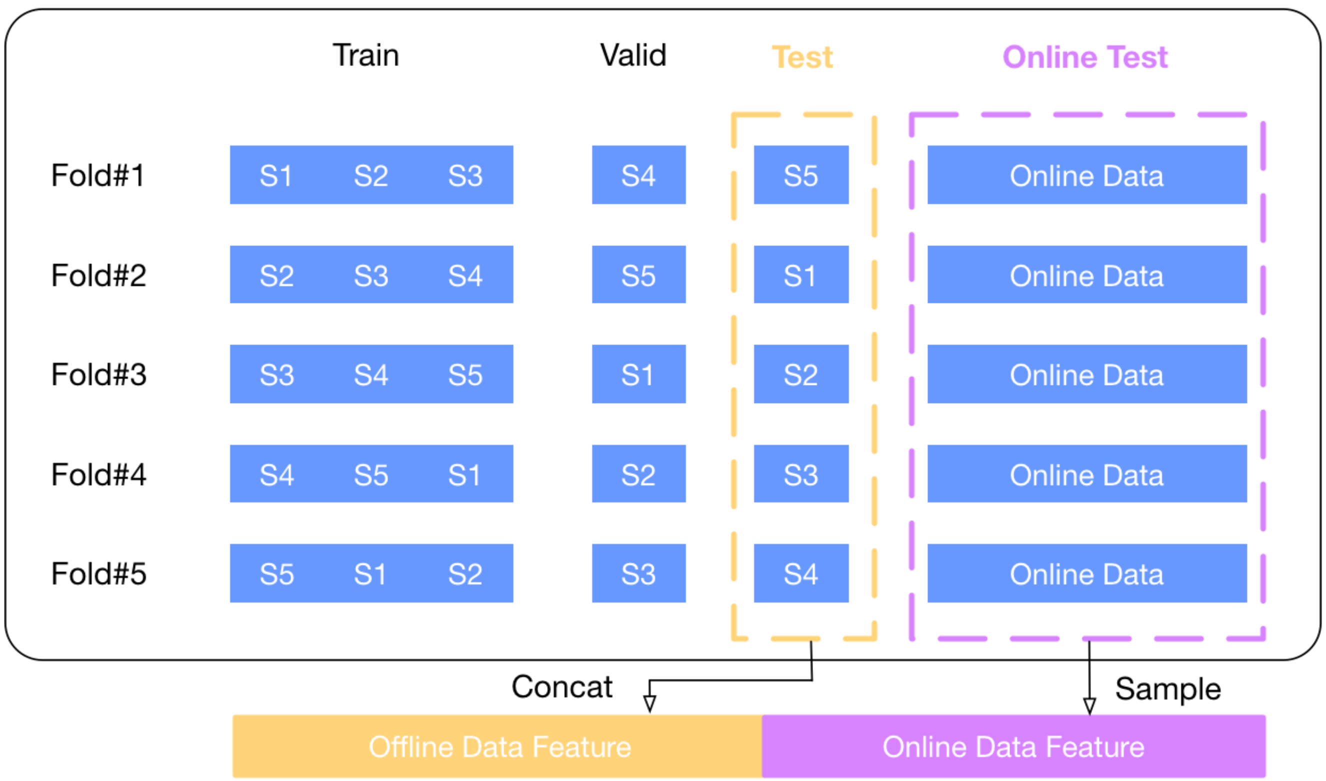
CHALLENGE

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



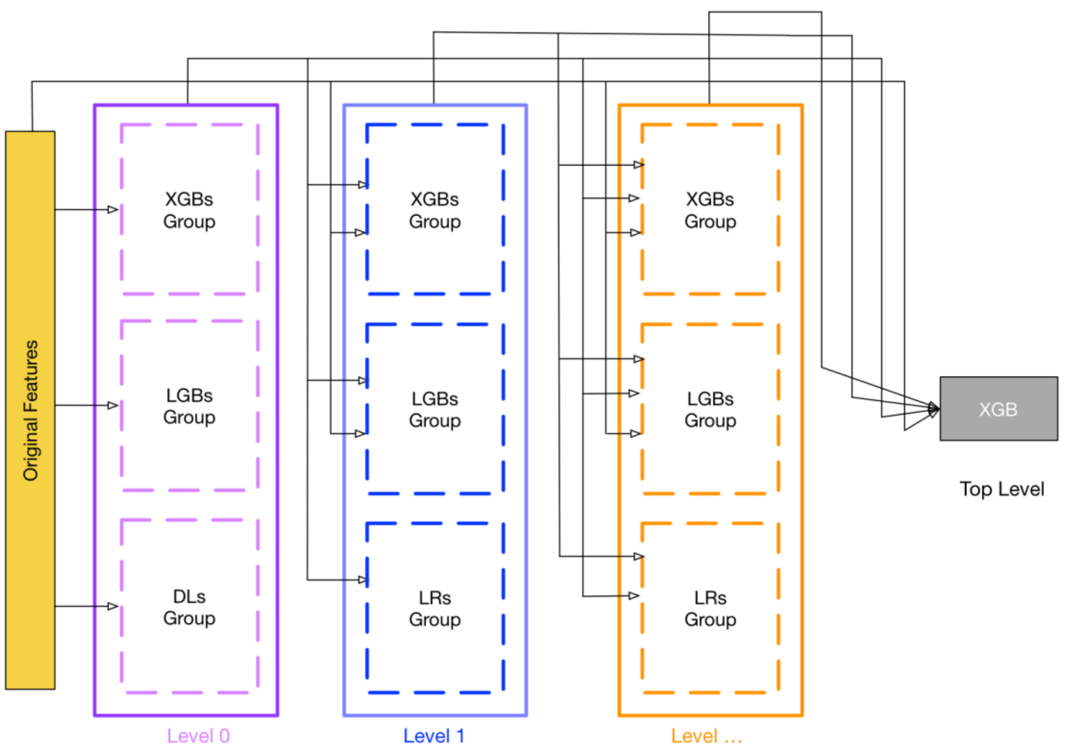
Deep Fusion • **Single Stacking**

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**

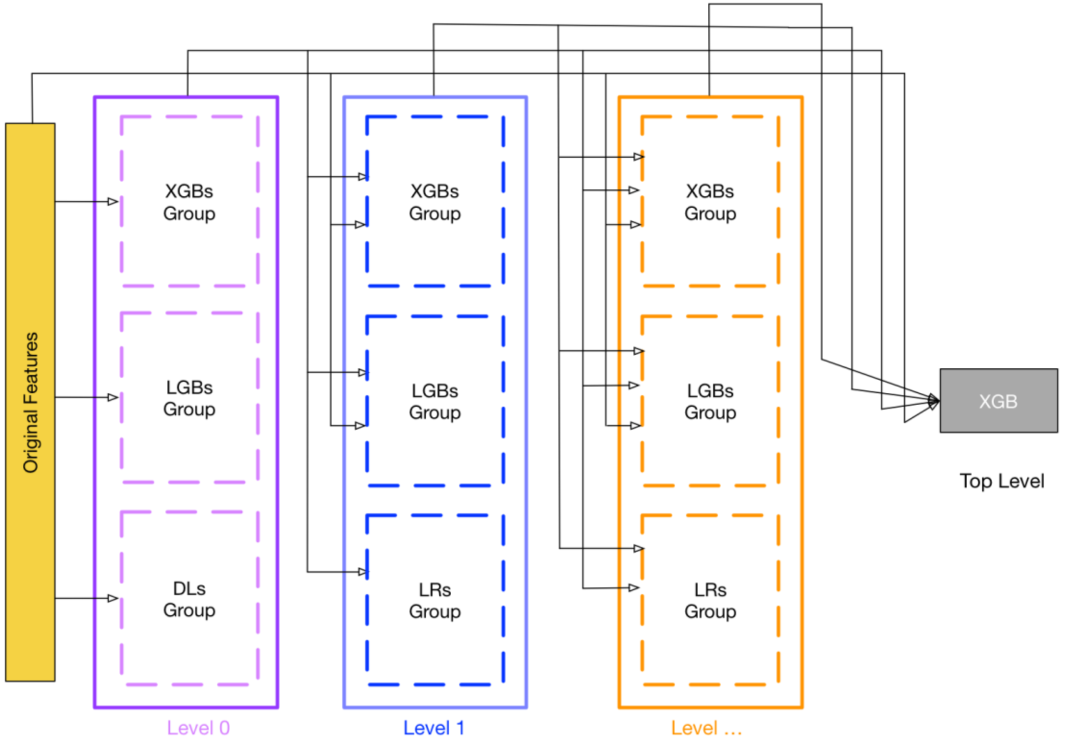
1. Fit and make predictions based on original features with diverse models.
2. Fit and make predictions based on **all** of the transformed features and **original** features with diverse models.



Deep Fusion • Cascade Stacking

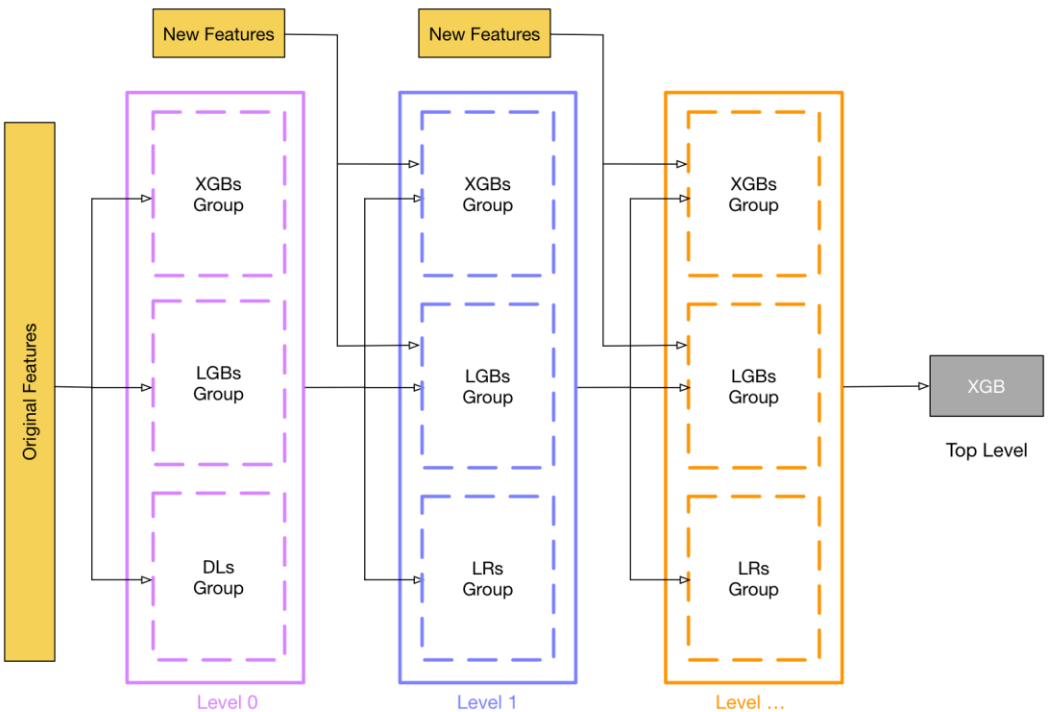
CHALLENGE

- 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.



Content

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

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.

Post-processing • **Split**

The standards of the division:

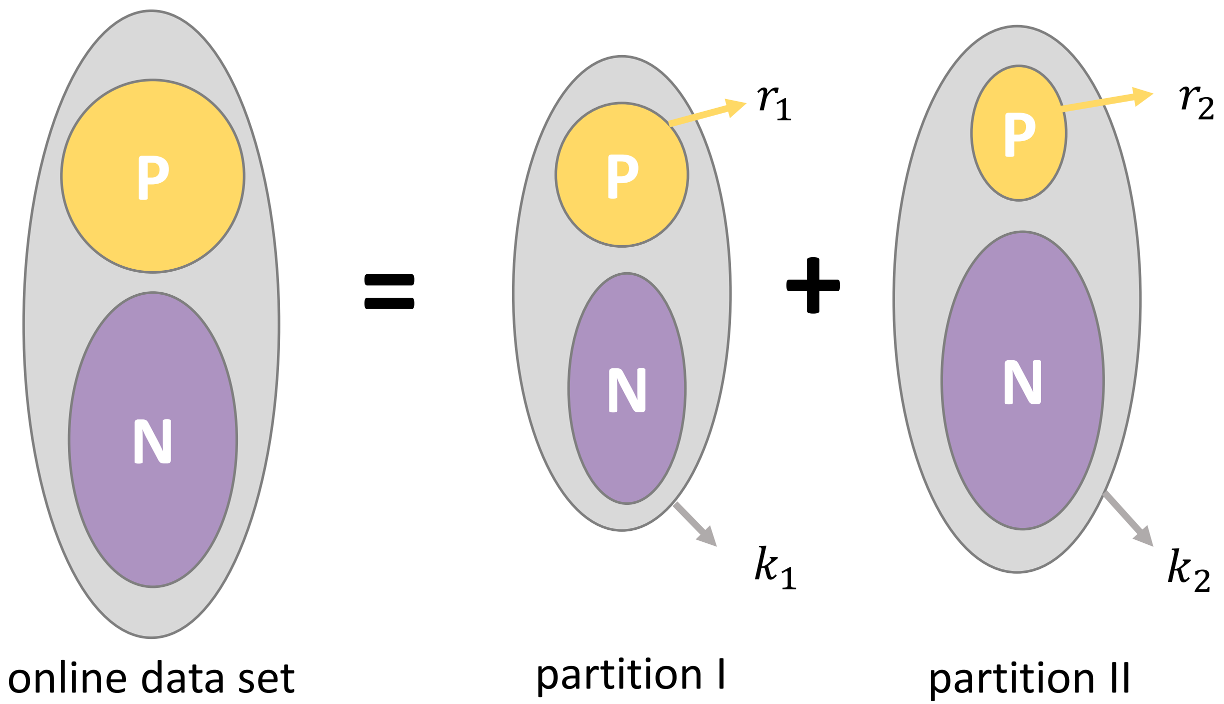
- graph_edge_max_clique_size (mc_size): Number of nodes contained in the largest clique of the edge.
- graph_edge_cc_size (cc_size): Number of nodes contained in the connected component of the edge.

	$mc\_size < 3$ $cc\_size < 3$	$mc\_size < 3$ $cc\_size \geq 3$	$mc\_size = 3$	$mc\_size > 3$
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.

$$k_1(r_1 \log v_{11} + (1 - r_1) \log v_{10}) + k_2(r_2 \log v_{21} + (1 - r_2) \log v_{20}) = -\text{score}$$



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

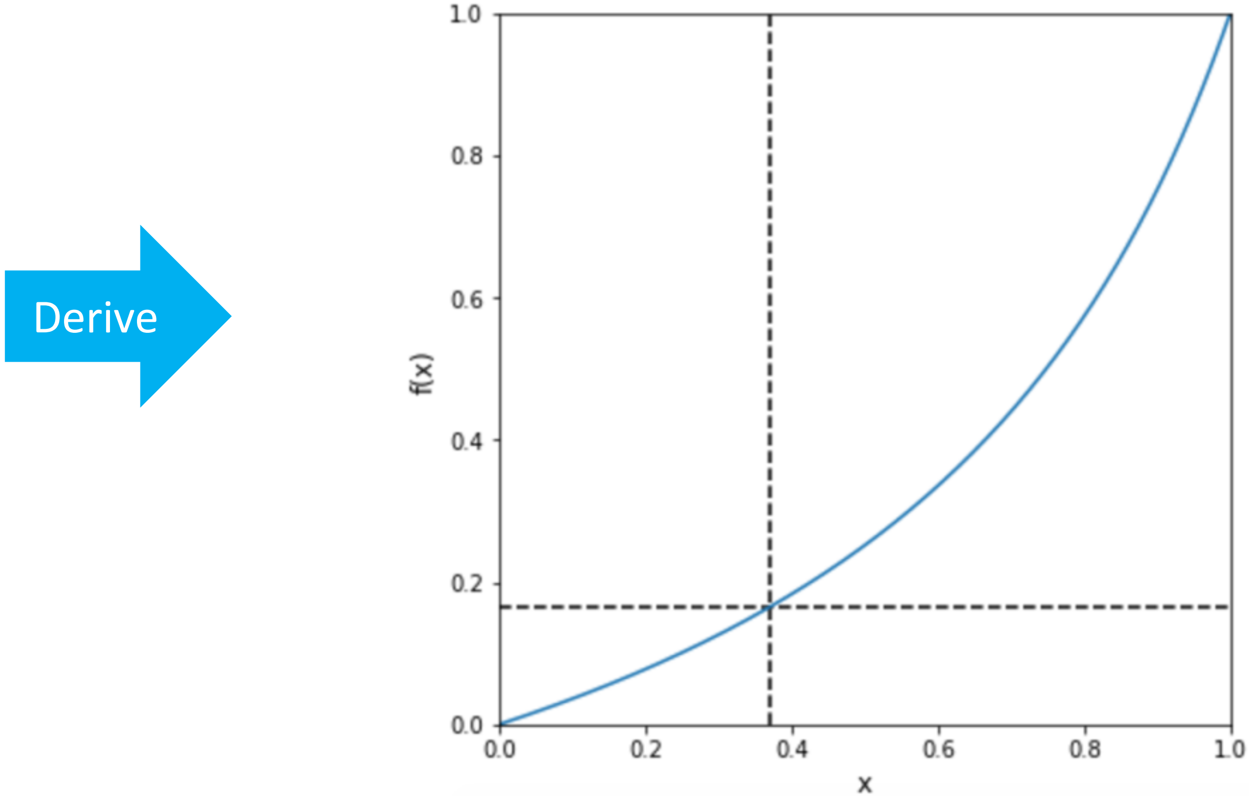
$$y_{rescale} = \frac{\frac{r_{online}}{r_{offline}} * y}{\frac{r_{online}}{r_{offline}} * y + \frac{1 - r_{online}}{1 - r_{offline}} * (1 - y)}$$

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.

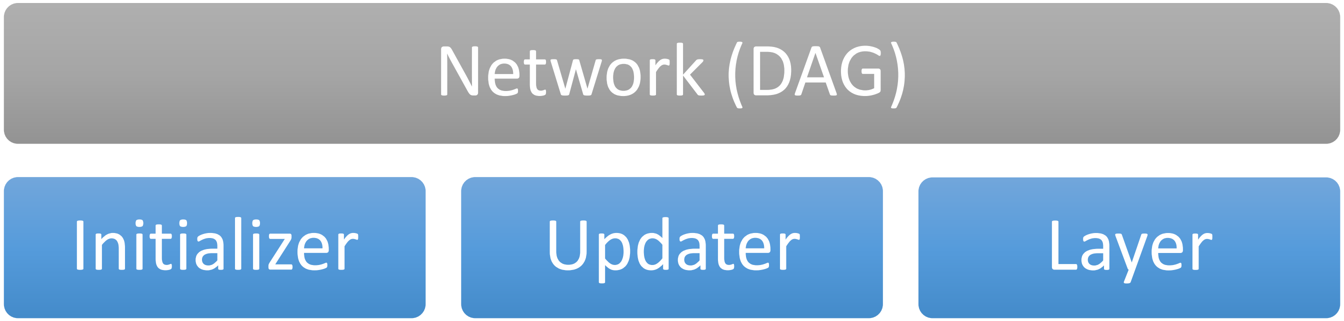
S Simple:
focus on extracting features and write a config file

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

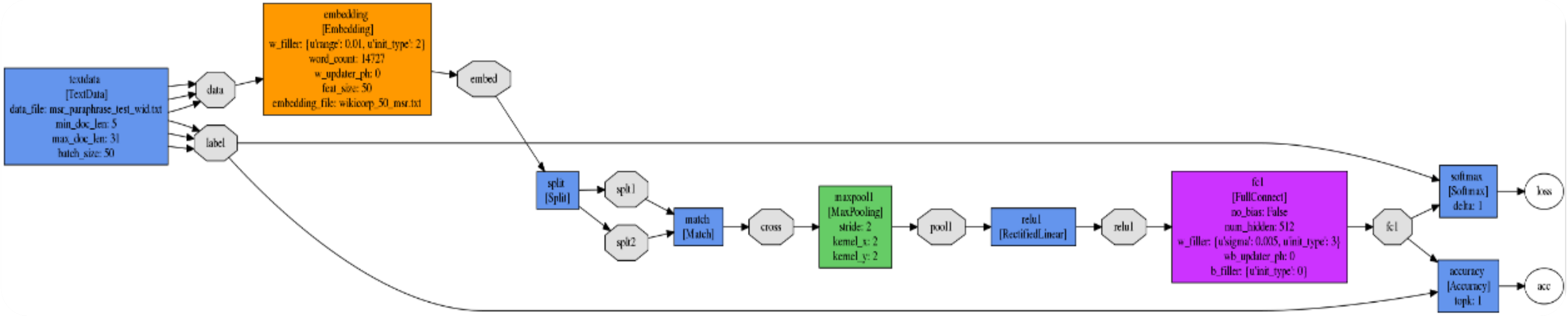
E Efficient:
generate index files to split the data set into training, validation and test

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

TextNet



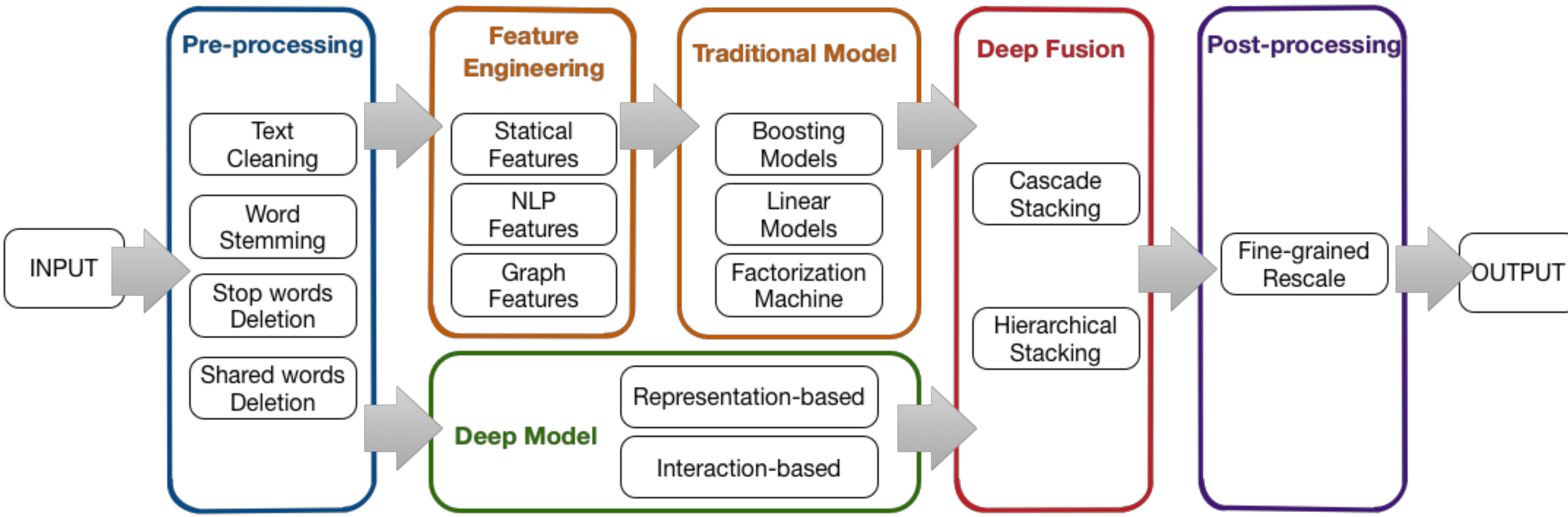
- Focus on text data, **Sparsity** and **Variance Length**.
- Support **JSON** config file to construct **DAG** networks.



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