A novel distributional semantic space model featuring quantum theories

Riling Li

Target: word similarity and association

- assess how well semantic model predict human judgments of word relatedness

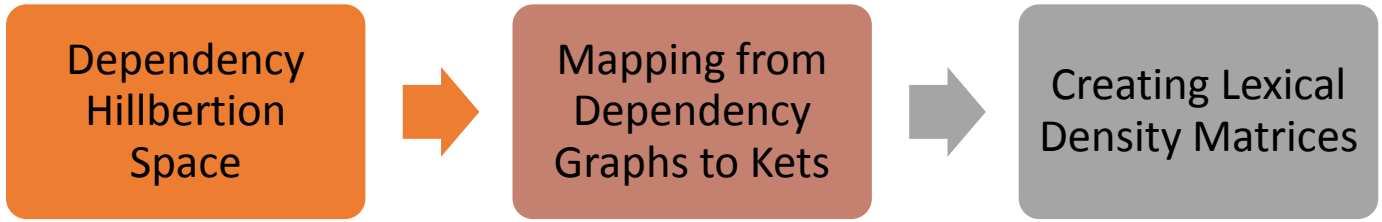
Data: wordsim353

- a test collection for measuring word similarity or relatedness, developed and maintained by E. Gabrilovich.

Results

- Correlations > 0.5, better than some other well-known models such as SDS & DM

Steps:



Questions:

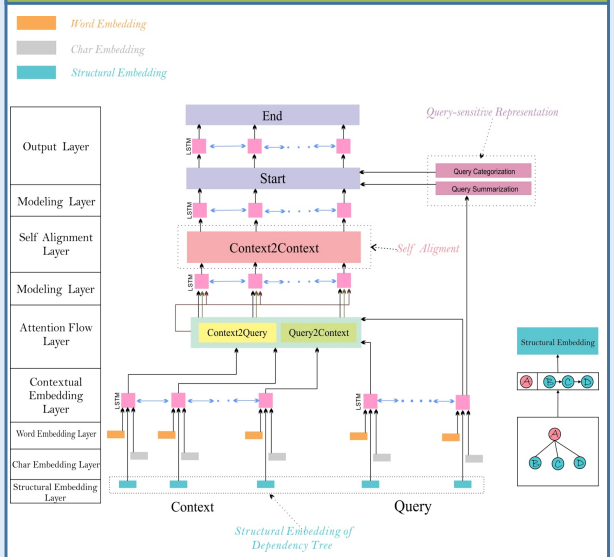
1. **Better performance?**
2. **Theoretic support?**

SSAE Model for Machine Comprehension

Ran Yi, Bin Hao

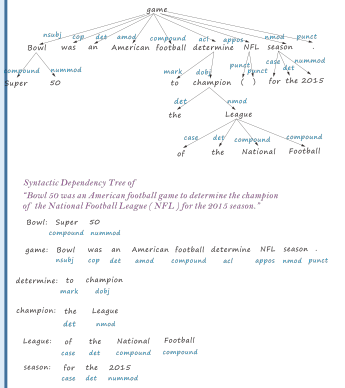
Goal: To find correct answer of well defined problems in the context of Stanford Question Answering Dataset (SQuAD).

Model Overview



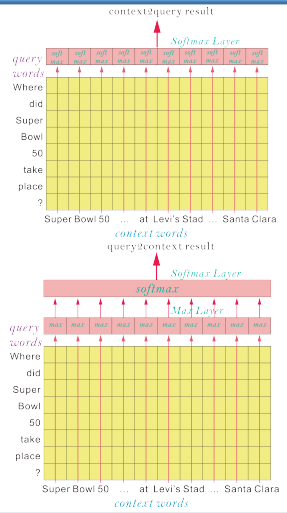
- A hierarchical and multi-stage machine comprehension model.
- Consisting of 7 Layers including structural embedding, attention flow, self alignment and pointer layers.

Step1: Syntactic Info Extraction

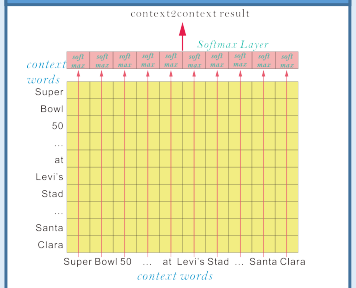


- Map each word to a vector using syntactic dependencies.

Step2: C2Q & Q2C Attention

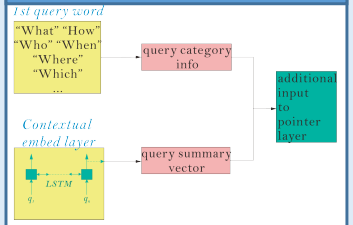


Step3: Self Alignment



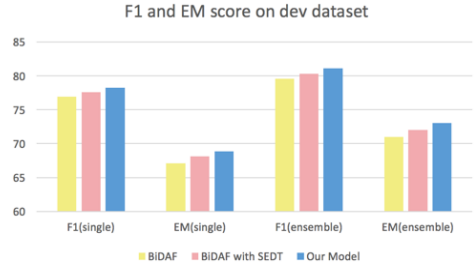
- Exploit contextual info within entire context paragraph.

Step4: Output With Explicit Query Info



- Utilize both explicit and implicit query info to predict boundary of answer.

Experiment Results



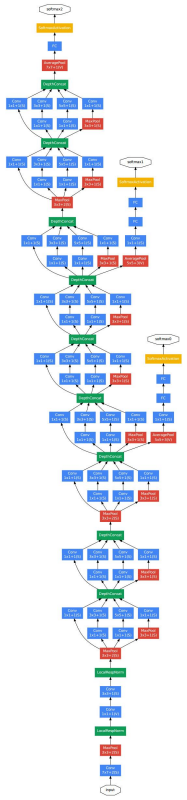
Method	Single				Ensemble	
	F1		EM		F1	EM
	max	mean	max	mean		
BiDAF	76.92	76.79	67.10	66.92	79.53	70.97
BiDAF +SEDT	77.58	77.42	68.13	67.89	80.28	72.03
Our Meho d	**78.26**	**77.88**	**68.89**	**68.52**	**81.07**	**73.03**

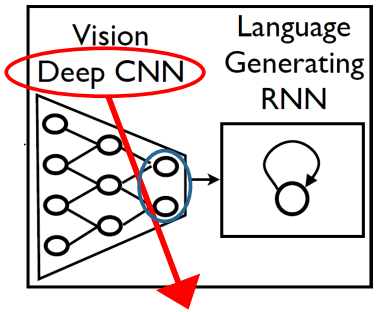
- Results on development dataset.
- Compare with BiDAF model and BiDAF model with SEDT.

Image Caption Tasks: Deep Features and Complex Model Mean Better?

Kaige Jia, Wenyu Sun, Bingyu Zhu
Department of Electronic Engineering, Tsinghua University

Vision Model: Deeper is Better?



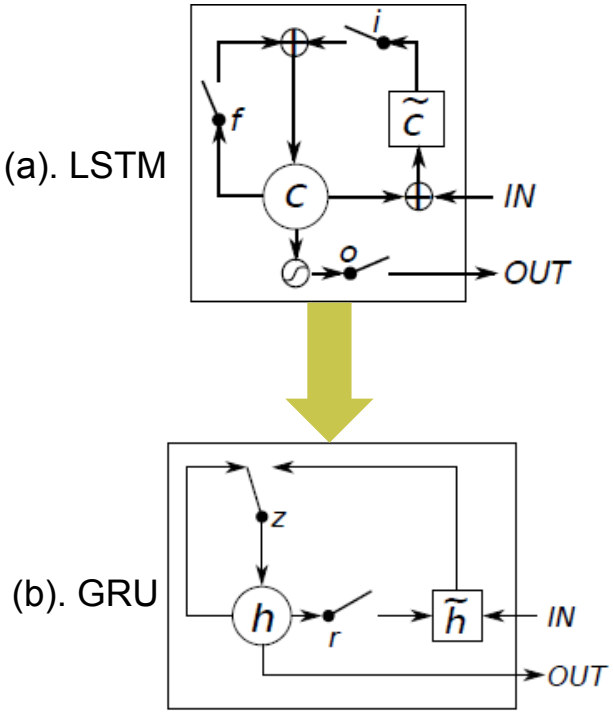


Last layer to output
Deeper is better?

type	patch size/stride or remarks	input size
conv	3×3/2	299×299×3
conv	3×3/1	149×149×32
conv padded	3×3/1	147×147×32
pool	3×3/2	147×147×64
conv	3×3/1	73×73×64
conv	3×3/2	71×71×80
conv	3×3/1	35×35×192
3×Inception	As in figure 5	35×35×288
5×Inception	As in figure 6	17×17×768
2×Inception	As in figure 7	8×8×1280
pool	8 × 8	8 × 8 × 2048
linear	logits	1 × 1 × 2048
softmax	classifier	1 × 1 × 1000

- Vision Model:
  - Google Inception V3 Net
- Input:
  - Figures from MSCOCO dataset
- Output:
  - Output of different layers to RNN

Language Model: LSTM->GRU



GRU vs LSTM

- GRU
  - ✓Without an extra memory cell
  - ✓Converge faster
  - ✓Performance is close to LSTM

Result

Table I
Scores on different layers of Google Inception V3 Net (LSTM model)

Metric	BLEU-4	METEOR	Rouge_L	CIDEr
Mixed_6b	0.225	0.212	0.478	0.685
Mixed_6c	0.234	0.219	0.487	0.725
Mixed_6d	0.256	0.23	0.504	0.806
Mixed_6e	0.273	0.243	0.518	0.89
Mixed_7a	0.276	0.243	0.519	0.892
Mixed_7b	0.283	0.247	0.524	0.925
Mixed_7c	0.268	0.238	0.512	0.876

Table II
Scores on different layers of Google Inception V3 Net (GRU model)

Metric	BLEU-4	METEOR	Rouge_L	CIDEr
Mixed_7a	0.278	0.243	0.52	0.896
Mixed_7b	0.285	0.249	0.526	0.941
Mixed_7c	0.263	0.238	0.51	0.866

Examples



7c: a man is standing on a snowboard in the snow （a man in a red jacket is snowboarding）
7b: a man riding a snowboard down a snow covered slope （a man is skiing down a snowy hill）
7a: a man riding a snowboard down a snow covered slope (a man riding a snowboard down a snow covered slope）
6e: a man is standing on a snowboard in the snow



7c: a man in a field with a frisbee in his hand (a man in a field with a frisbee)
7b: a young boy playing with a frisbee in a field (a man laying on the ground with a frisbee in his hand)
7a: a young boy is playing with a soccer ball (a man is playing frisbee on a field)
6e: a man is sitting on the grass with a Frisbee

双分支网络做图文匹配

清华大学电子工程系　李天鹏，万纬韬

新闻

乒超 联赛 山东 击败 八一 马龙 未 上场 球队 险胜 对手 北京 时间 12月 25日 消息 2016-2017 赛季 中国 乒超 联赛 男团 第 18 。。。

TF-IDF

训练：以负样本相似度减去正样本相似度的差为优化目标

两层全连接网络

512维向量空间

两层全连接网络

VGG网络fc8特征向量



推断：与新闻相似度最高的图片为新闻的配图

A System For Maching Text News With Corresponding Recommended Images

Danyang Sun , Bin Wu

2017,6,5

Introduction

Introduction:

- system of matching text news with top n corresponding recommend pictures..
- put both the image and the text in the same feature space,.
- word2vec and LSTM.
- pre-trained deep convolution network

Dataset and Problem Definition

Dataset

- provided by Sohu.
- 100000 pieces of news and their corresponding pictures.
- very complicated, which includes real images, comics, printing fonds, QR code and so on..

Problem Definition

- a set of M text news $T_M = \{t_1, t_2, ..., t_M\}$
- a set of N images $I_N = \{i_1, i_2, ..., i_N\}$
- mapping function $F : t \to P$, where t is an element of set T_M and I is a subset of I_N.
- address the relations about texts and images.

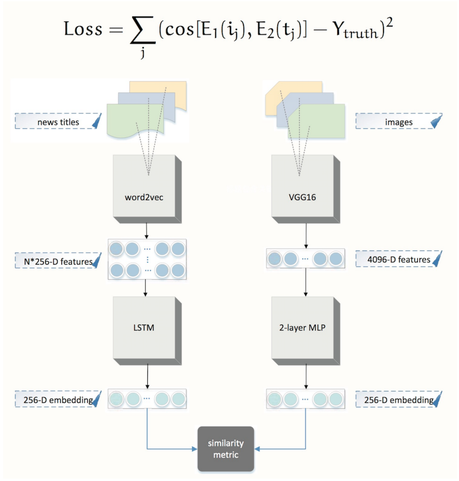


Figure 1: Model Pipeline

Model Description

Image Embedding:For a Image I, we use a deep convolution neural network as a feature extractor. We choose a pre-trained VGG-16 network classifier, and exclude the last 1000 neural fully connected layer and the softmax layer to get a 4096 dimension feature embedding.

Text Embedding:we pre-train a word2vec model using all the text data and Chinese wiki, then a 256 dimension embedding of the title is obtained from the model. After that, we use a LSTM and get a 256 dimension output vector.

Cosine Distance:We use the cosine distance to measure the similarity of these two 256 dimension vector embedding, one from the image and the other from the text.

Loss Function

$$Loss = \sum_j (cos[E_1(i_j), E_2(t_j)] - Y_{truth})^2$$

equation (1) and the whole system is illustrated as in Fig **??**.E_1 and E_2 means the embedding of the text and the image, i_j means the j^{th} image and t_j means j^{th} text (title). $Y_{truth} = 1$ for the positive example and 0 for the negative example.

Training Effect

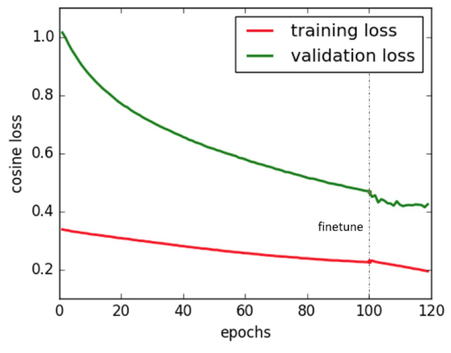


Figure 2: Model Pipeline

Experiments and Results

During the training process, we fix the VGG16 network, and train the whole network 100 epochs.

Then we fine-tune the VGG16 network 20 epochs to get better performance. During the experiment

we take the text and its corresponding image as the positive input, and we construct some negative examples ourselves.

The proportion of the positive and negative examples is 1:2.

Result of Model

Average ranking	
100	28/100
1000	209/1000

Figure 3: Model Evaluation

ndcg@1	ndcg@2	ndcg@3	ndcg@4	ndcg@5
0.0039893	0.0090233	0.0096882	0.011979	0.014551
ndcg@6	ndcg@7	ndcg@8	ndcg@9	ndcg@10
0.017867	0.020083	0.02050	0.02050	0.021656

Figure 4: Model Evaluation

reasonable example

配置并不低 静态体验林肯MKX 2.0T尊享版

[搜狐汽车导购]林肯MKX的出现,为那些希望选购50万左右SUV车型的消费者们又提供了一个新的选择。而林肯MKX拥有两个排量(2.0T以及2.7T)共四款车型。。。



Figure 5: Model Pipeline

Summary and conclusions

- Image data is too complicated including nature images, comics, printing fonds, QR code and so on, we don't train an accurate prior-classifier.
- The training tend to get not-bad results,not useful results.
- Evaluation time cost is expensive. If we have n image-text pairs, the complexity is $O(n^2)$.
- Build a system for matching text news with corresponding recommended images which can be also used to bidirectional retrieval.
- Practise the pipeline of building an actual machine learning model, from data clean, build model, debugging, finetune to finally realize.
- Feel a sense of accomplishment and happiness when model works.

A Study of Entity Embedding for Entity Search

LiuZhengHao TuWei



A. Design

- Capture the semantics of entity properties and relations to other entities

B. Develop

- **Accurate** and **efficient** entity retrieval models

C. Potential Solution

- FSDM Model
- Yan et al Model

D. Data Categories

- **INEX_LD**
- **ListSearch**
- **SemSearch ES**
- **ListSearch**

E. Promotion

- Enhance the effect of **1.5 – 7 times** than baseline

Final Project Madness

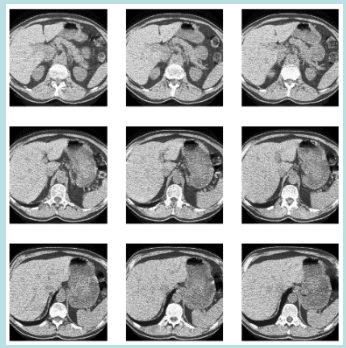
2017.06

Applying Deep CNN and Boosting Tree to the Solution of Lung Cancer Detection

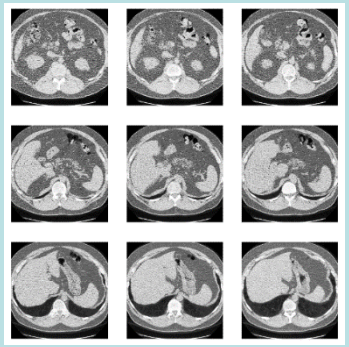
Li Jiahao Wang Chenxin

Data Preprocessing

a. Raw data

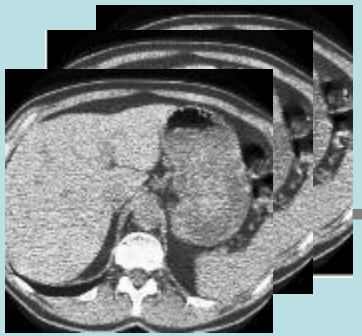


a.1 patient with lung cancer



a.2 patient without lung cancer

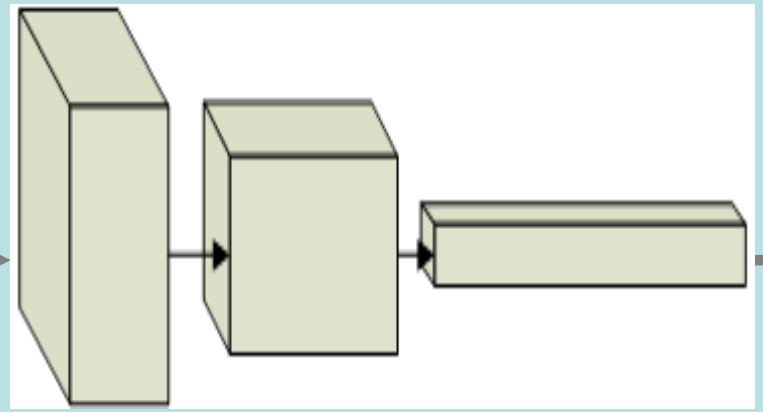
b. preprocessing



Combine three adjacent slices into 3-channel input data

Feature Extraction

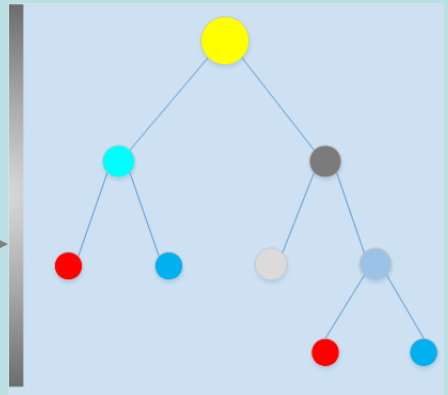
Resnet-n convolutional neural network



Apply pre-trained Deep CNN on CNTK, here Resnet-18 adopted, to the feature extraction, removing the last softmax layer

Classification

Boosting tree for classification



Yes

Lung Cancer?

No

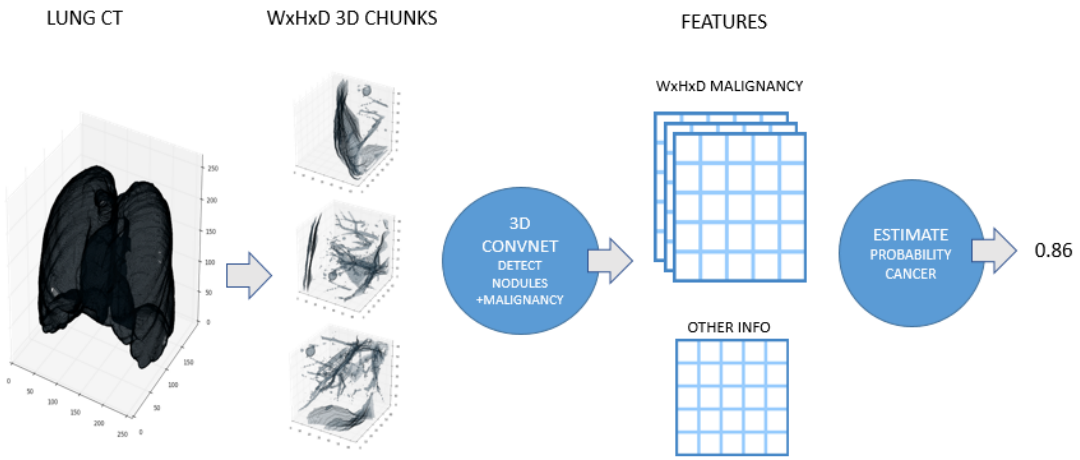
Utilize the feature from CNN to train a boosting tree for classification and make the prediction on the test data

Lung Cancer Detection

SUN XIAOQING, ZICHAO ZHOU
Department of Computer Science and Technology

- The dataset is not big enough to train the model.
- From raw images to labels couldn't work
- Without background information.

- Using luna16 dataset and LIDC dataset.
- Nodule detectors would be helpful .
- Doctors' comments can be a important feature.

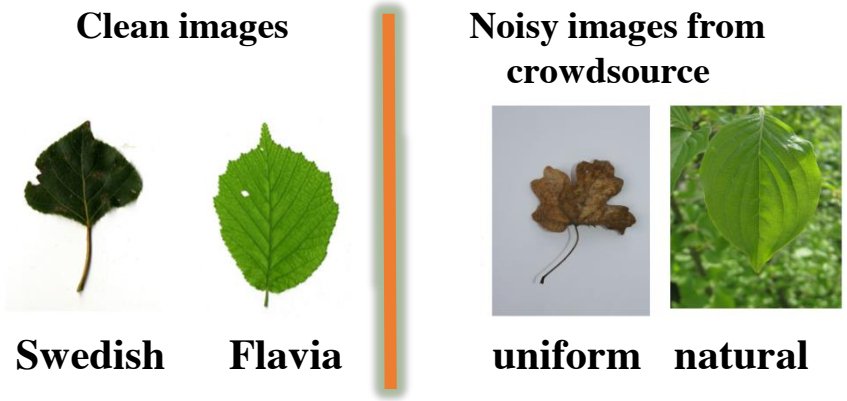


Automatic Leaf Recognition - Liu Dong & Kefan Chen

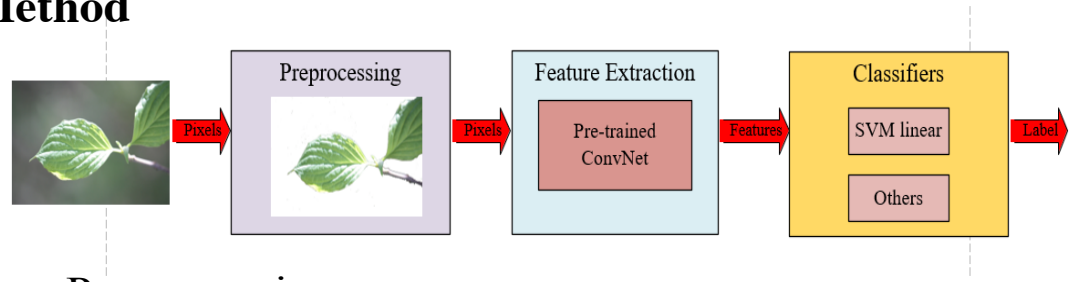
➢ Problem

- Automatic leaf recognition has important applications, but with great difficulties.

➢ Dataset



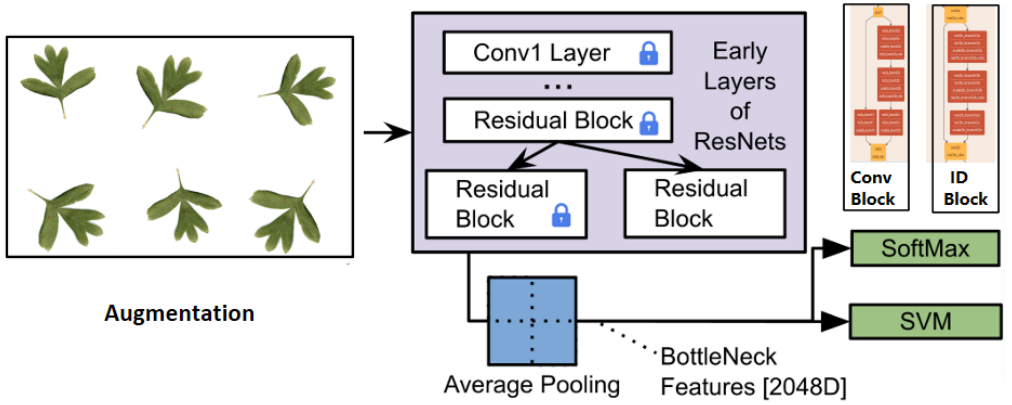
➢ Method



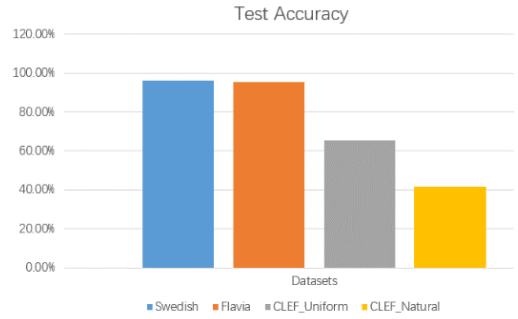
- Preprocessing
- Feature Extraction – ConvNet
- Classification

➢ Transfer Learning – ConvNet

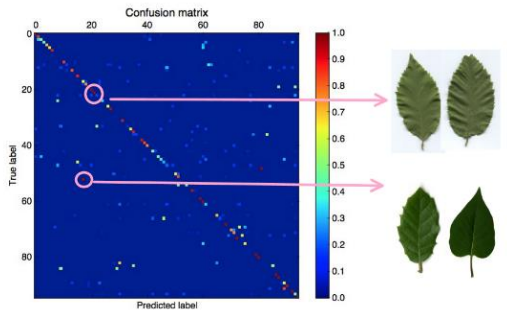
- ResNet50



➢ Experimental Results



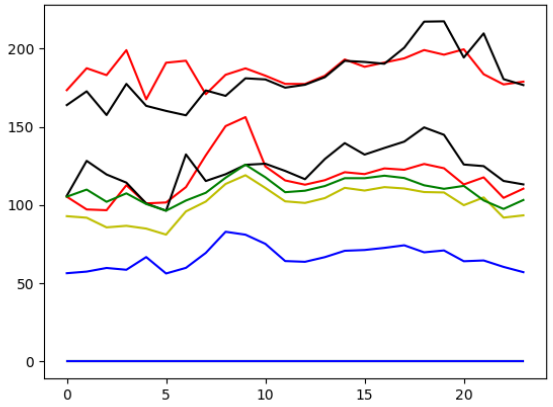
Test Accuracy



Confusion Matrix

Predict Travel Time Through a High Way

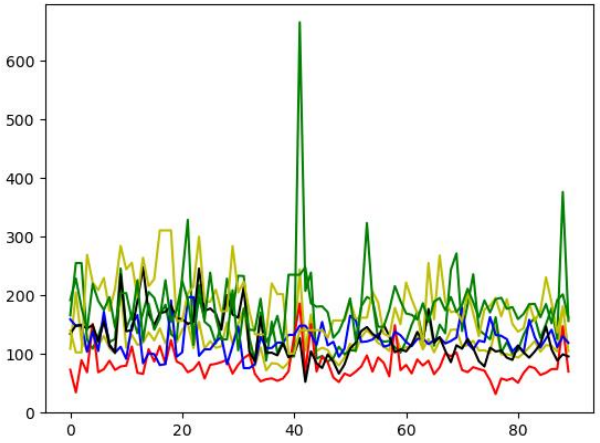
Li Haoda, Yuan Haitao, Wang Haiquan



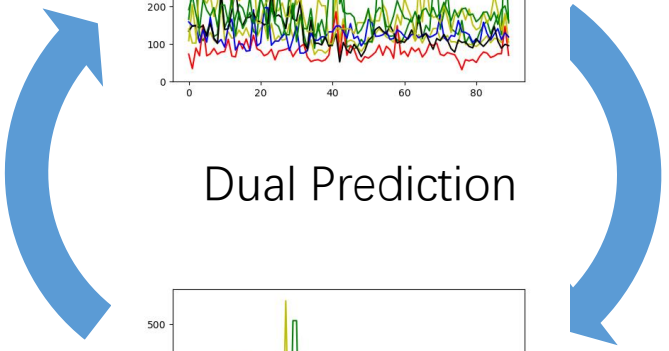
Stable trends

+

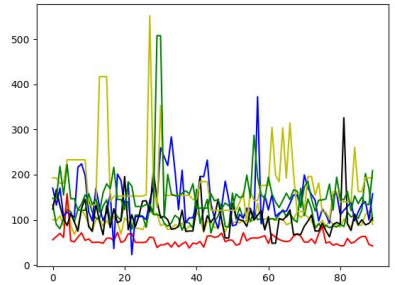
Extreme case



+



Dual Prediction



Gradient Boost Tree x LSTM

ANIMATION HEAD PORTRIT GENERATION WITH CONDITIONAL GENERATIVE ADVERSARIAL NETWORKS

Input: simple animation characters scripts

Output: enriched animation images

Objective Function:

$$\mathcal{L}_{cGAN}(G,D) = \mathbb{E}_{x,y\sim p_{data}(x,y)}[\log D(x,y)] + \mathbb{E}_{x\sim p_{data}(x),z\sim p_z(z)}[\log(1 - D(x, G(x,z))]$$

Try and draw it yourself !



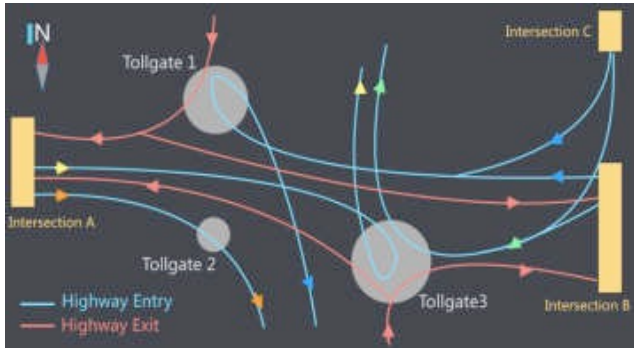
line 1: edges from original images

line 2: generated images from edges

line 3: original images

Highway Tollgates Traffic Flow Prediction

Mingye Song, Lin Ma



Original Data

Feature Selection

Features	Description	Type
$speed_b$	the average speed 20m before	time
$volume_b$	volume 20m before	time
weekday	weekday of this week	time
fastigium	the fastigium degree of this road	time
$volume_i$	volume into the road 20m before	time
$volume_o$	volume out of the road 20m before	time
$width_m$	minimum width of the road	road
lanes	lanes of the road	road
precipitation	the precipitation of the day	road
$volume_a$	volume from all intersections	geographical

Features

Model Design

Model	offline	online
KNN	0.232	0.230
Random Forest	0.1976	0.2011
Extra-tree	0.1956	0.1984

Results

Time, Geographic, Road

Ensemble Methods
1. Stacking
2. Clustering+LR

Wednesday at 07:00am, FIT building, Final Presentation for Advanced ML Course

Research on Fine-grained Entity Typing

Yuji Yang, Xiaokun Zhang
Dept. of Computer Science and Technology

Do you think the [mention] below is a (sports_team) ?
Every word in the context please give a confidence value between 0 and 1.

It	was	won	by	the	[Ottawa Senators]	,	coached	by	Dave	Gill	.
0.7	0.7	0.7	0.7	0.7		0.7	0.7	0.7	0.7	0.7	0.7
0.1	0.1	0.9	0.6	0.6		0.5	0.8	0.4	0.1	0.1	0.0

Method1: context vectors
Method2: attentive context vectors

Fast Portrait Automatic Segmentation with Coarse-to-Fine CNNs

Ruilong Li, Wenqi Ouyang, Xin Dong

Real-time: 40fps!

Segmentation IOU: 96.38% !

Network: two stage!

- course (VGG4)!
- fine (googlenet)!

Loss: multi-task!

- edge loss!
- mask loss!

Methods	Mean IoU
FCN-8s(person class) [4]	48.37%
PortraitFCN [3]	89.25%
FCN-8s(our dataset) [4]	91.86%
FCN with Googlenet(our dataset)	93.05%
Our coarse network	94.48%
Coarse network(no auxiliary loss)	94.00%
Our fine network	**96.38%**
Fine network(no coarse channel)	95.02%

Person Re-identification with Generative Color-Invariant Feature

Guangyi Chen, Zehao Zhang

Motivation: person images across multiple camera views are variance in visual appearance caused by varying lighting conditions.

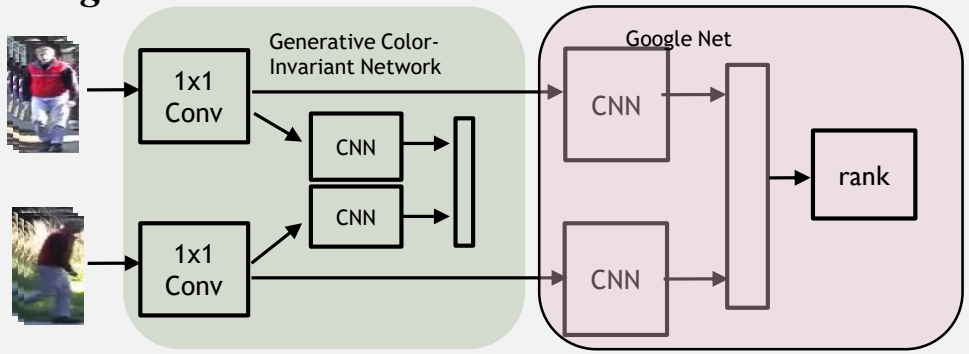
***Color-Invariant*:**

$$\begin{bmatrix} R^r \\ G^r \\ B^r \end{bmatrix} = C\left\{\begin{bmatrix} R^u \\ G^u \\ B^u \end{bmatrix}\right\} = \begin{bmatrix} \beta_1 & 0 & 0 \\ 0 & \beta_2 & 0 \\ 0 & 0 & \beta_3 \end{bmatrix}\begin{bmatrix} R^u \\ G^u \\ B^u \end{bmatrix} + \begin{bmatrix} o_1 \\ o_2 \\ o_3 \end{bmatrix}$$

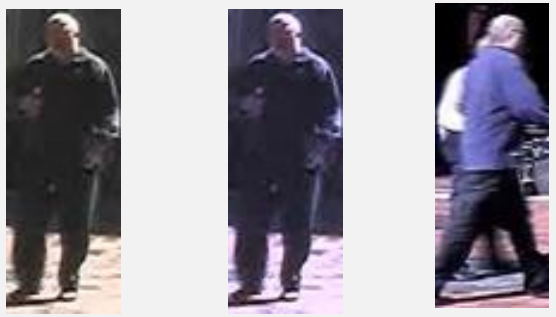
$$L^D = -E_x[\log D(X)] - E_x\left[\log\left(1 - D\left(C(x)\right)\right)\right]$$

$$L^C = -E_x\left[\log\left(D\left(C(x)\right)\right)\right]$$

***Ranking based CNN*:**



Examples of Color-Invariant



X : Cam A **Color Invariant** **Y : Cam B**

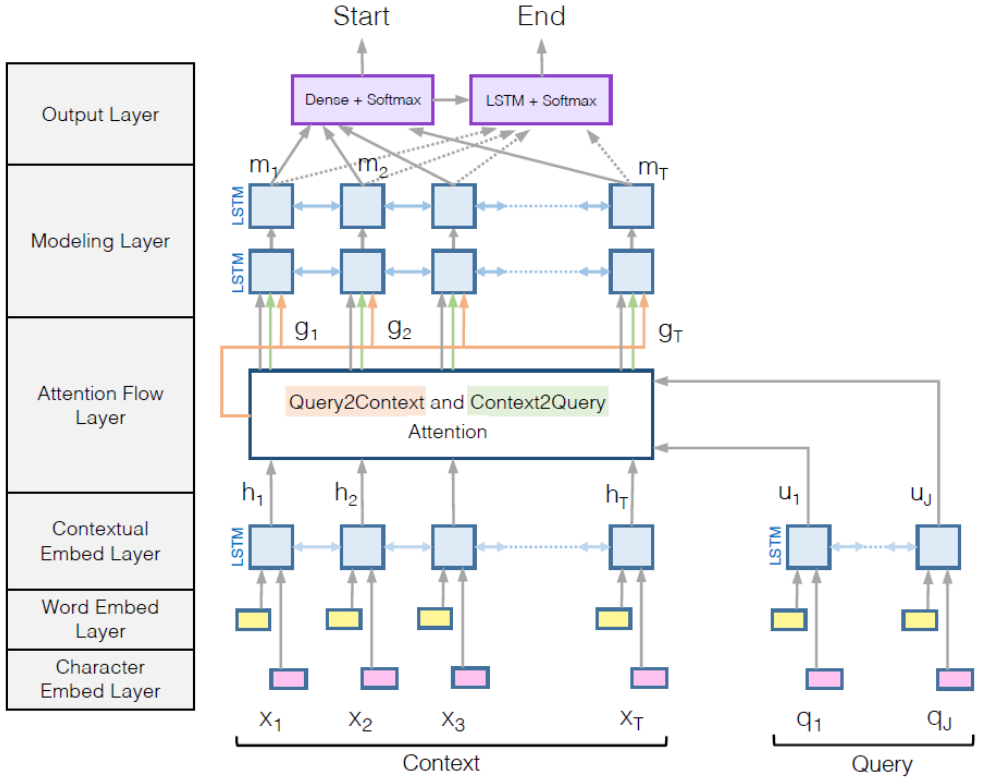
$$X' = C_x C_y^{-1}(X)$$

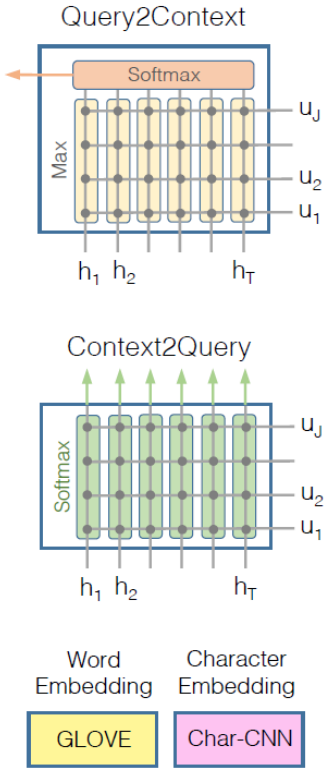
***Rank 1 Accuracy*:**

	CUHK03	CHUK01	VIPeR
LSSCDL[1]	57.0	65.97	42.97
FT-JSTL+DGD[2]	75.3	66.60	38.60
Ours (Two stage)	84.0	71.43	48.32
Ours (End to End)	87.1	73.37	47.15

Stanford Question Answering

Yanzhuo Ding, Xiaobin Ma





Query-to-Context Attention

$$\tilde{\mathbf{h}} = \sum_t \mathbf{b}_t \mathbf{H}_{:t}$$

Context-to-Query Attention

$$\tilde{\mathbf{U}}_{:t} = \sum_j \mathbf{a}_{tj} \mathbf{U}_{:j}$$

Training

$$L(\theta) = -\frac{1}{N} \sum_i^N \log(\mathbf{p}^1_{y_i^1}) + \log(\mathbf{p}^2_{y_i^2})$$

Experiments

Exact Match (EM)

F1 score: Weighted average of the precision and recall rate at character level

	EM	F1
Logistic Regression Baseline	40.4	51.0
BIDAF	66.9	76.7

References:

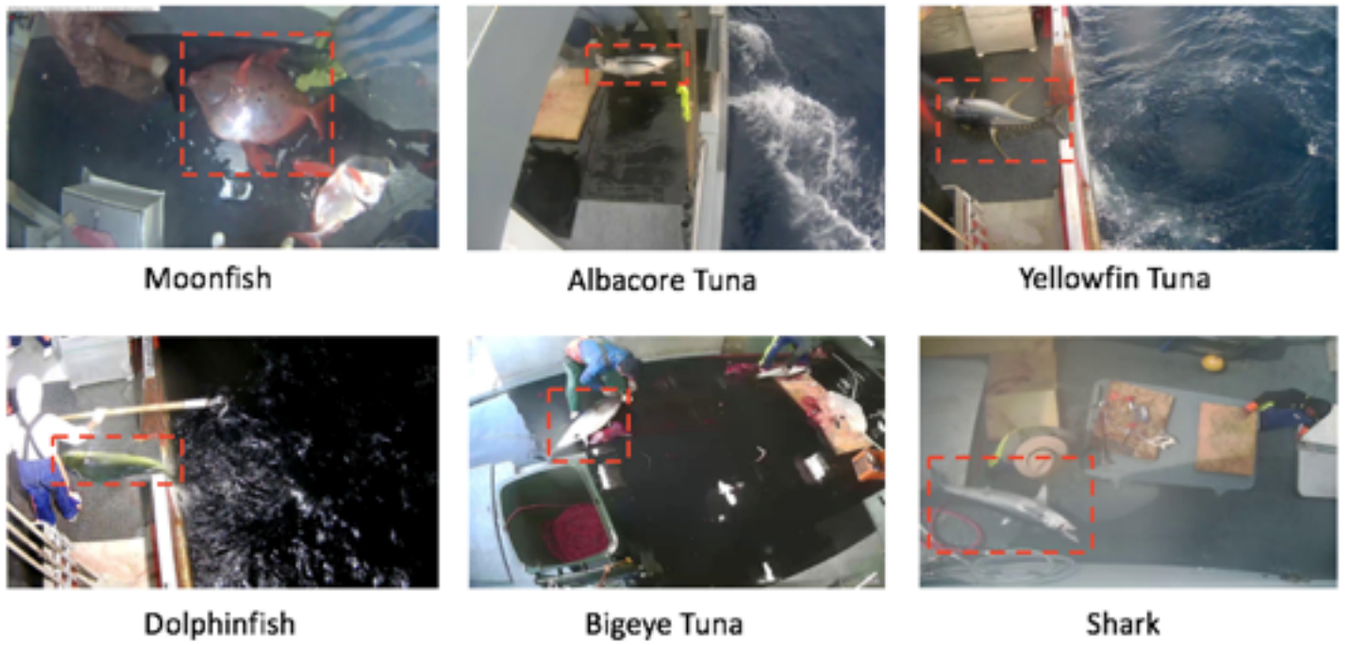
Minjoon Seo, Aniruddha Kembhavi, Aniruddha Kembhavi and Hananneh Hajishirzi**. Bi-directional attention flow for machine comprehension.** ICLR, 2017.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. **Squad: 100,000+ questions for machine comprehension of text.** In EMNLP, 2016.

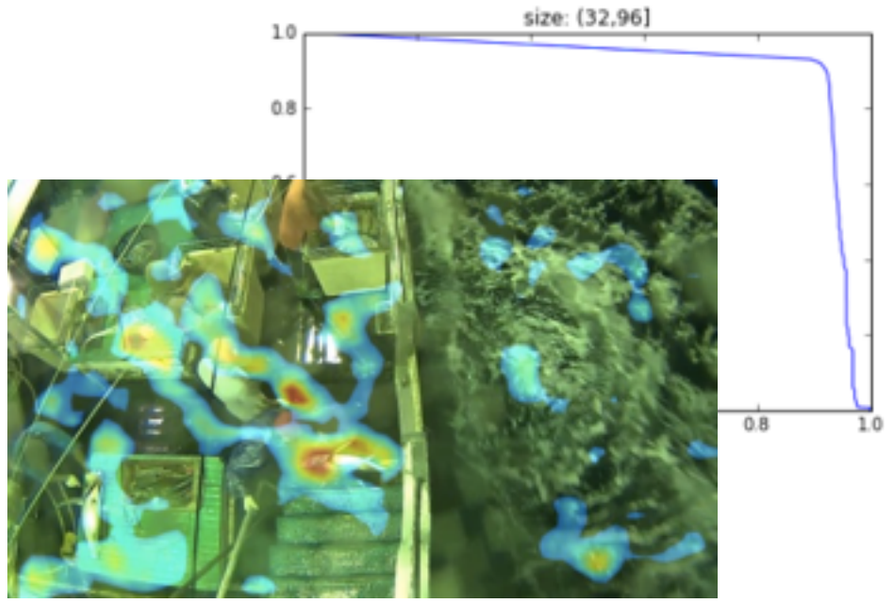
The Nature Conservancy Fisheries Monitoring

Weinan Shi, Yunfei Lu

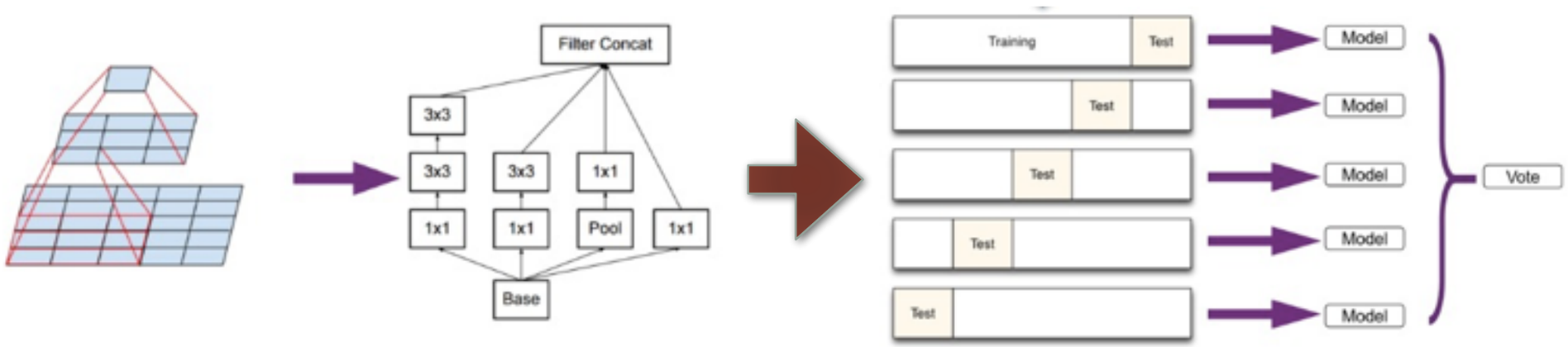
Image Classification with poor data



Fast R-CNN



Inception v3 and boosting



Other Attempts

Boat clustering
Complementary data
XGBoost
AlexNet CNN model
Overfeat

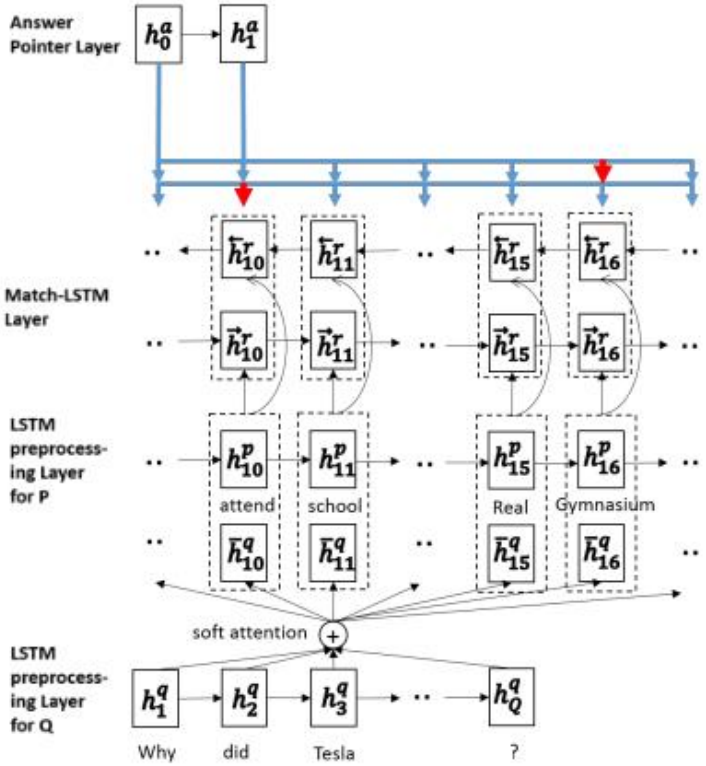
logloss=2.0176

logloss=1.9584

Rank 185

Stanford Question Answering

Huazhe Lou, Hao Wang



Match-LSTM

$$\overrightarrow{G_i} = \tanh(W^q H^q + \text{tile}(W^p h_i^q + W^r \overrightarrow{h_{i-1}^r} + b^p))$$

$$\vec{\alpha}_i = \text{softmax}(w^T \vec{G}_i + \text{tile}(b))$$

$$\vec{z}_i = \begin{bmatrix} h_i^p \\ H^q \vec{\alpha}_i^T \end{bmatrix}$$

$$\overrightarrow{h_i^r} = \overrightarrow{\text{LSTM}}(\vec{z}_i, \overrightarrow{h_{i-1}^r})$$

$$H^r = \begin{bmatrix} \overrightarrow{H^r} \\ \overleftarrow{H^r} \end{bmatrix}$$

Answer Pointer

$$F_k = \tanh(V\tilde{H}^r + \text{tile}(W^a h_{k-1}^a + b^a))$$

$$\beta_k = \text{softmax}(v^T F_k + \text{tile}(c))$$

$$h_k^a = \overrightarrow{\text{LSTM}}(\tilde{H}^r \beta_k^T, h_{k-1}^a)$$

$$p(a|H^r) = p(a_s|H^r) p(a_e|a_s, H^r)$$

Loss function

$$-\sum_{n=1}^{N} \log p(\alpha_n | P_n, Q_n)$$

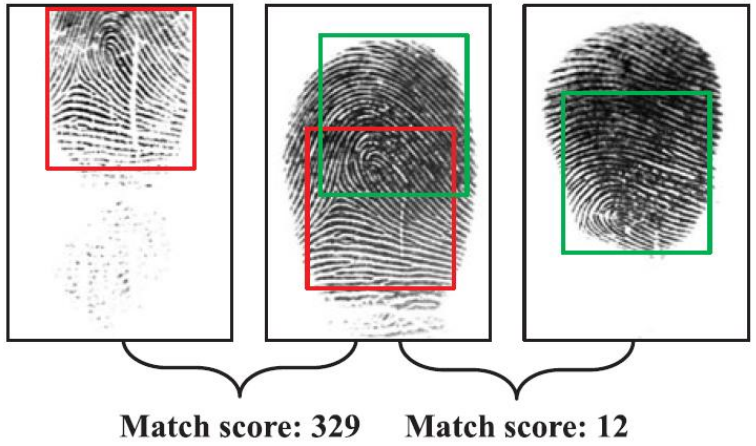
	F1	EM
Logistic Regression Baseline	51	40.4
Our Model	60.16	48.69
r-net (ensemble)	84.01	76.92

Reference

[1]Wang, Shuohang, and Jing Jiang. "Machine comprehension using match-lstm and answer pointer." , *arXiv preprint arXiv:1608.07905 (2016).*
[2]Vinyals, Oriol, Meire Fortunato, and Navdeep Jaitly. "Pointer networks." *Advances in Neural Information Processing Systems. 2015.*

Rectification of Distorted Fingerprints

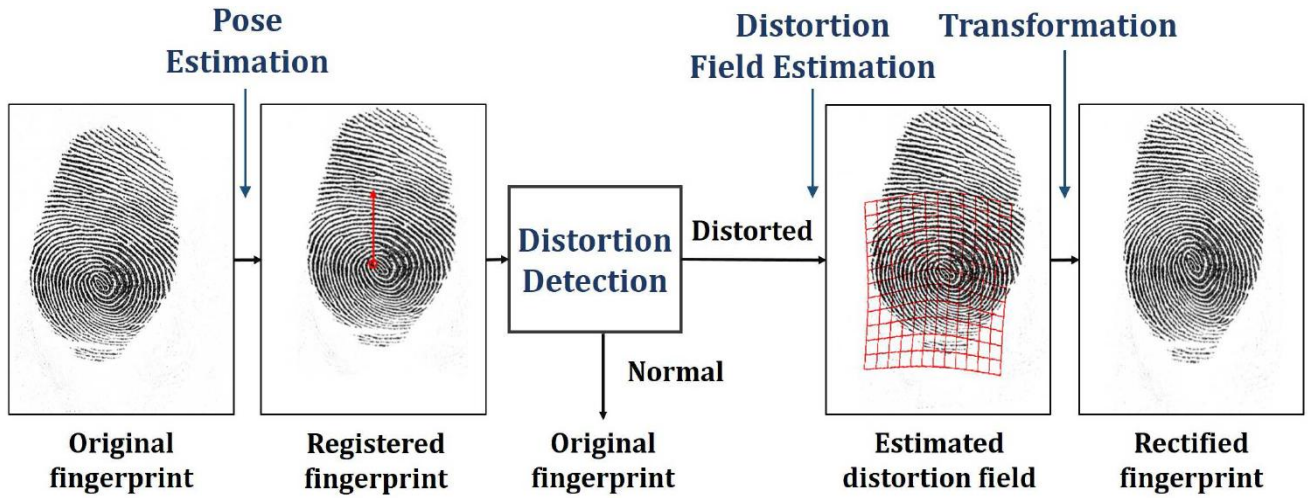
Shaowen Zeng, Shan Gu



Distortion greatly influences the recognition rate

➡

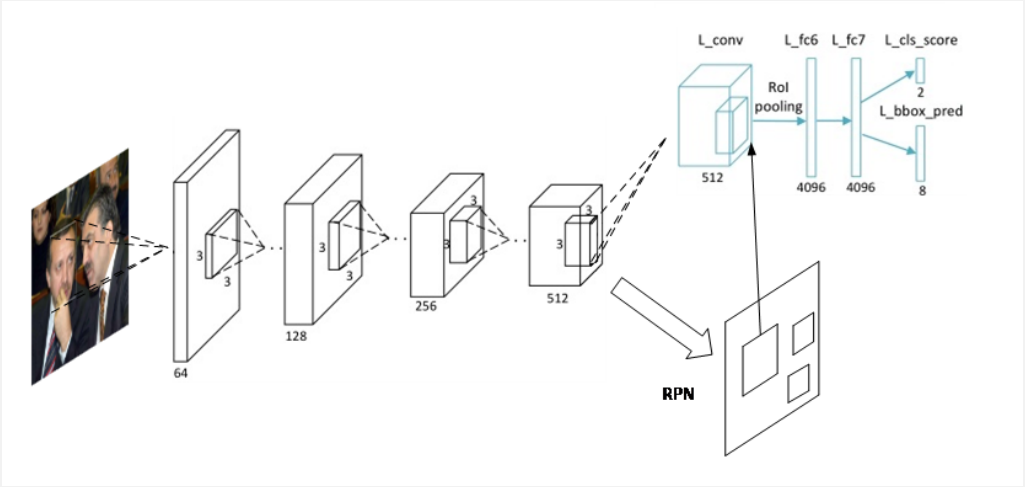
fast **distortion rectification** method to transform a distorted fingerprint into a normal one



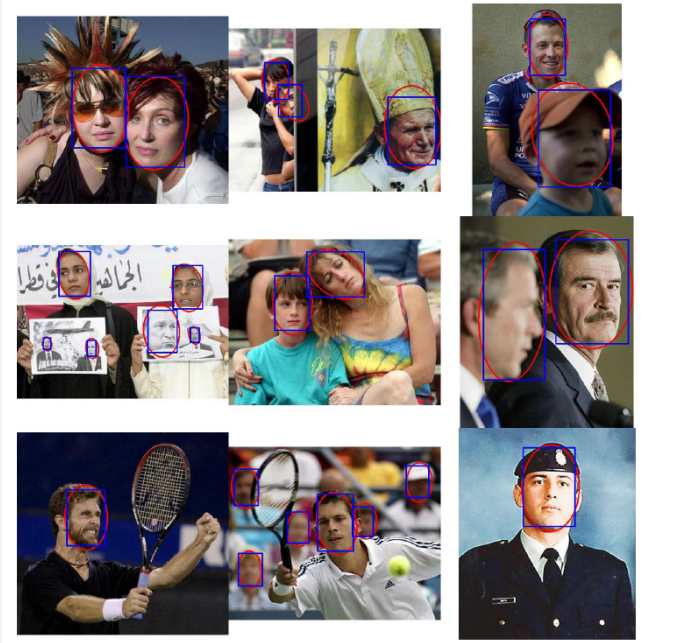
- A **faster R-CNN** based pose estimation
- A **CNN** based feature extraction
- A **classification** based distortion detection
- A **regression** based distortion field estimation

Face Detection Using Improved Faster RCNN

李子焱 韩纪飞



Faster RCNN framework



Selected detected faces (red: annotation; blue: detection result)

- We improve the state-of-the-art faster RCNN framework by combining a number of strategies.
  - Feature concatenation
  - Online hard example mining
  - Multi-scale training
- Achieve the nearly state-of-the-art detection performance on FDDB face detection benchmark evaluation.

	continuous			discrete		
	100	500	1000	100	500	1000
our	0.6939	0.7277	0.7328	0.9151	0.9619	0.9682
HR	0.6408	0.6816	0.6879	0.9058	0.9613	0.9698
HR-ER	0.7403	0.7844	0.7903	0.9102	0.9688	0.9764

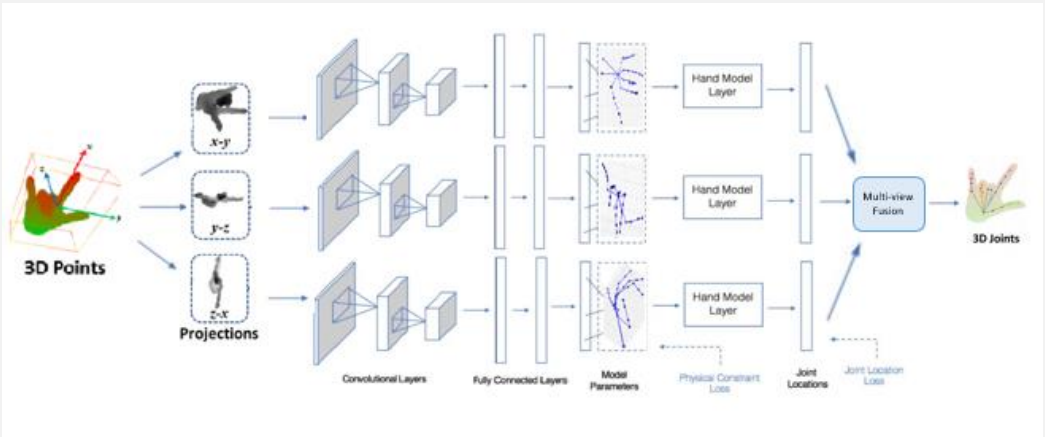
FDDB benchmark results

Human Hand Pose Estimation

Xin Yuan, Liangliang Ren, Chunze Lin

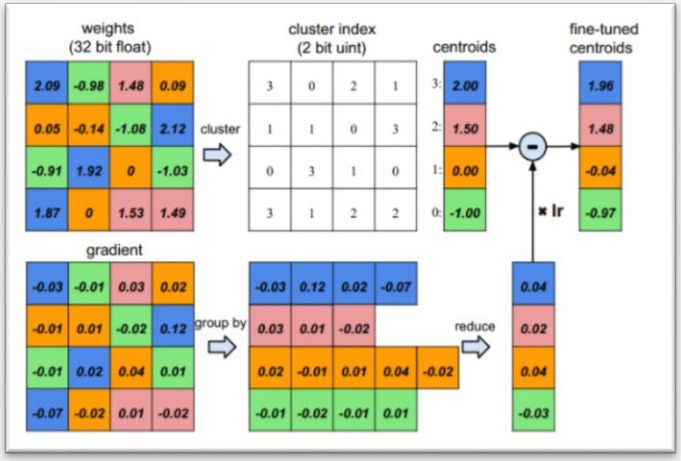
Hand Pose Estimation is important for applications in human-computer interaction (VR/AR).
Difficulties: Self-occlusion, Multiview changes…

We propose the deep learning model:



- Projection of depth image into 3 orthogonal planes
- Feed to convolutional layers
- Fuse Multiview information for final hand pose estimation

Ease the implementation of this model in small equipment: Deep Compression



16 weights originally but only 4 shared weights: similar weights are grouped together to share the same value

Predicting 2-dimensional shallow water wave using Deep Spatio-Temporal Residual Networks

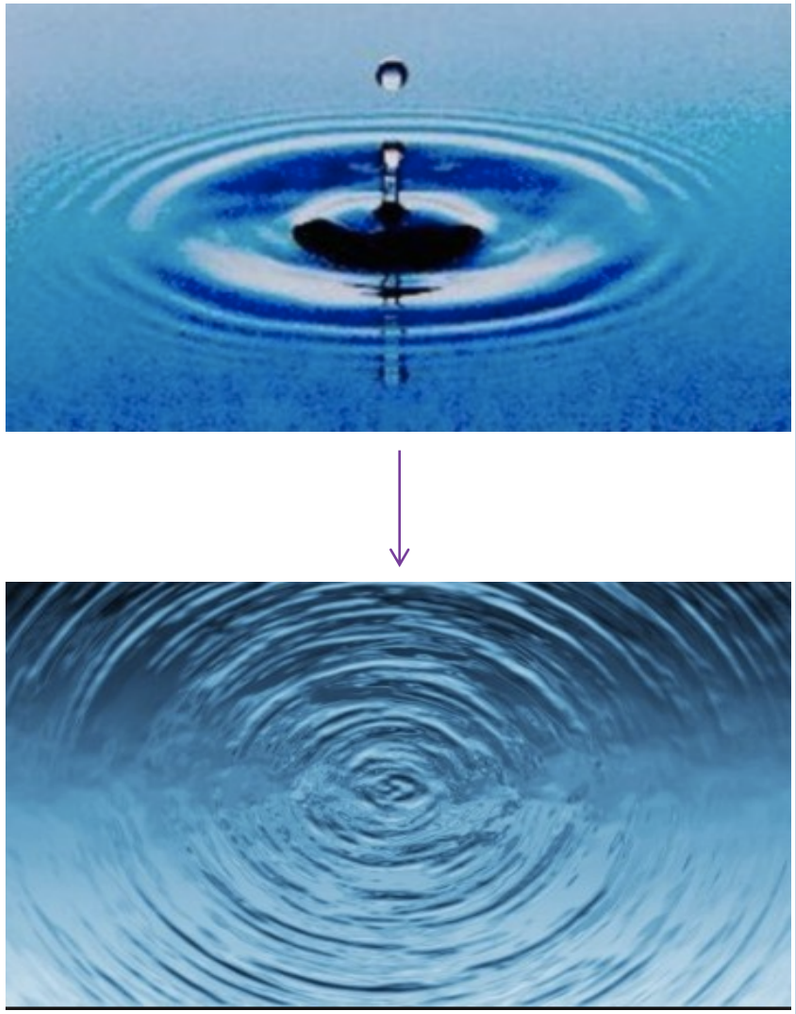
Qi Wu, Maocai Xia
Department of Earth System Science

Shallow water equations

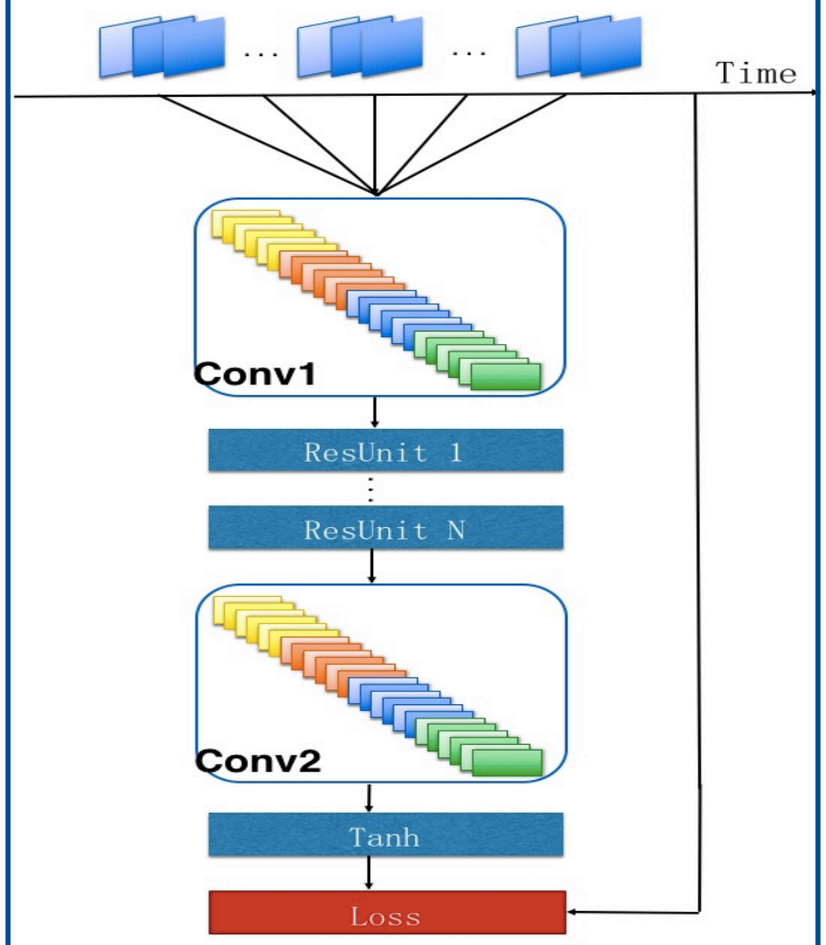
$$\frac{\partial h}{\partial t} + H\left(\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y}\right) = 0,$$

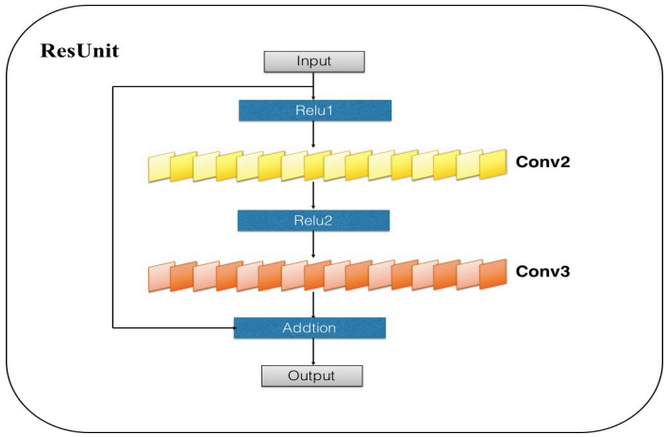
$$\frac{\partial u}{\partial t} - fv = -g\frac{\partial h}{\partial x} - bu,$$

$$\frac{\partial v}{\partial t} + fu = -g\frac{\partial h}{\partial y} - bv.$$

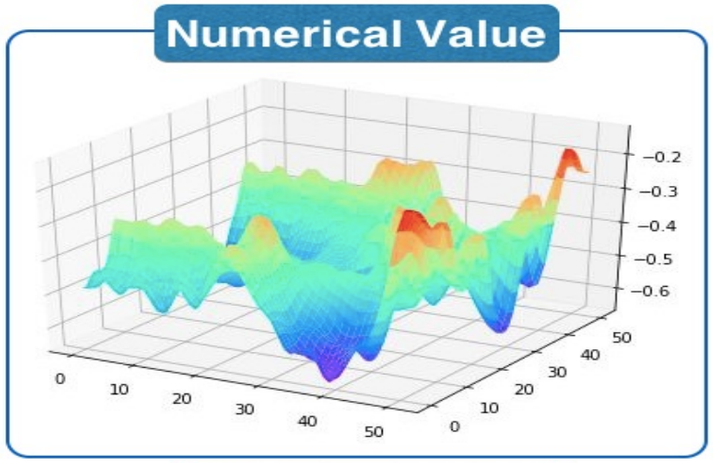


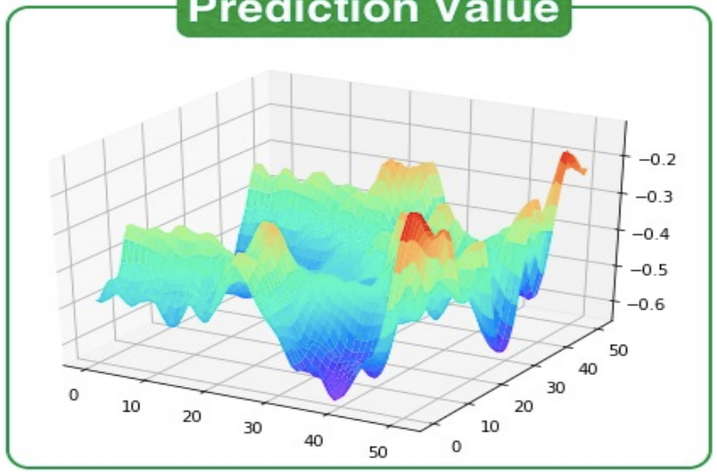
ST-ResNet

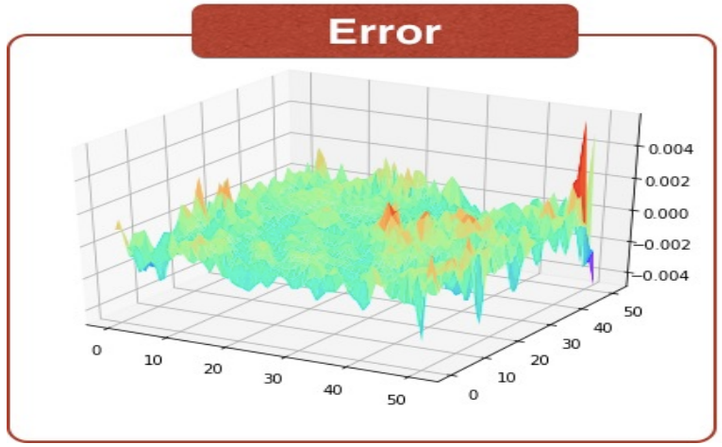




Results

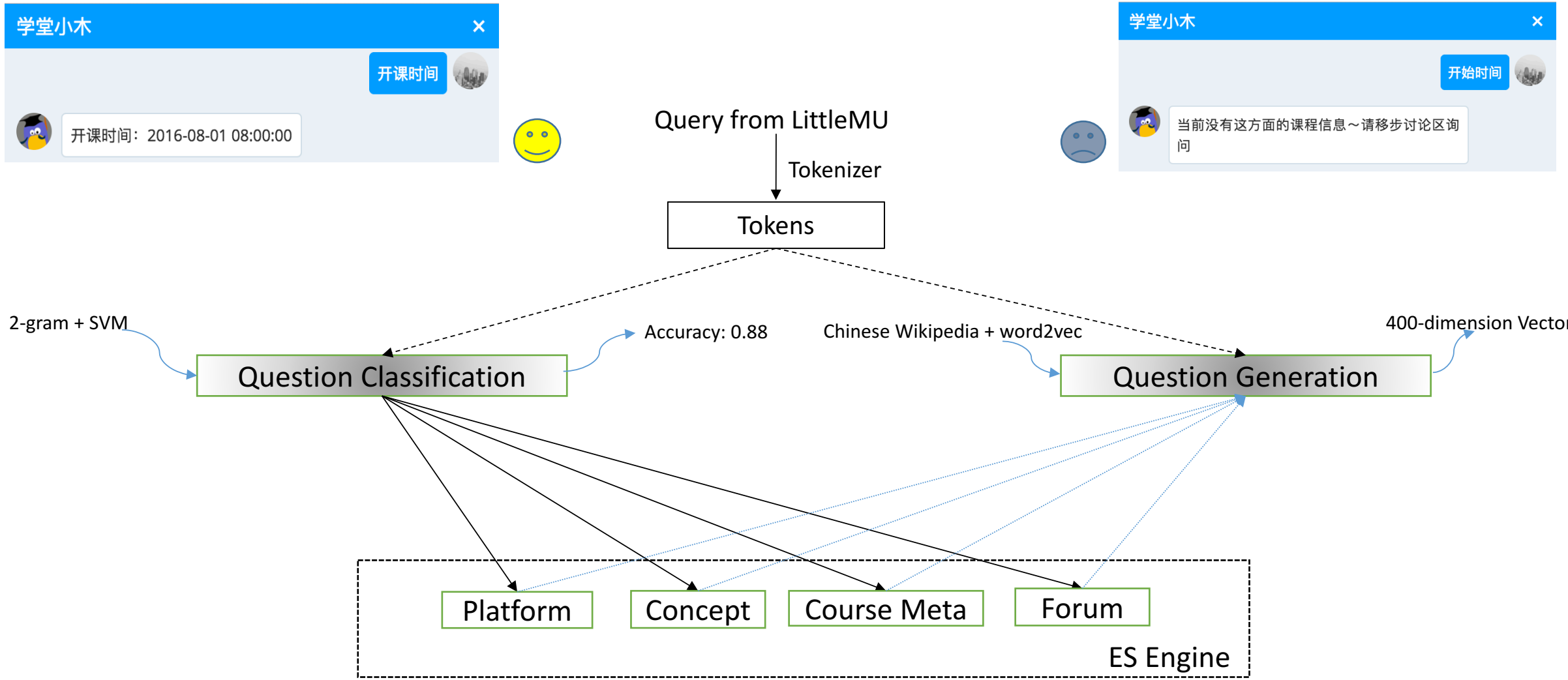






Question Classification and Question Generation in Question Answering System

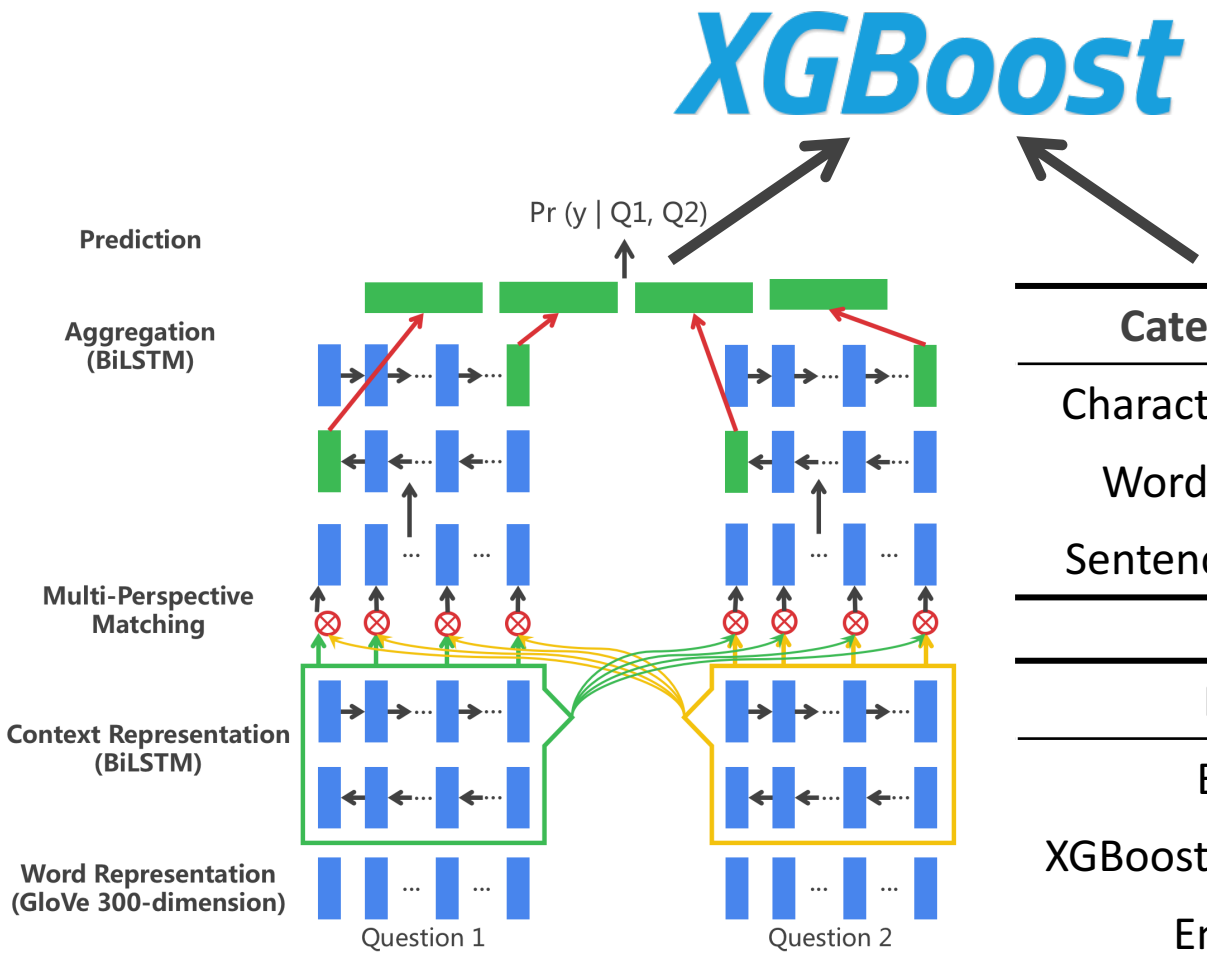
Zhengyang Song, Jiao Sun



Predicting Quora Question Pairs Based on Ensemble of Deep Learning and XGBoost

Tongtong Liu, Yihan Wang

- Multiple questions with same intent cost seekers and writers more time.

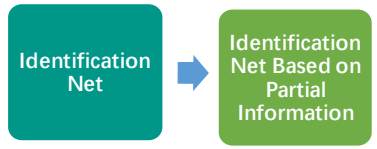


Category	Features
Character-level	11
Word-level	21
Sentence-level	15

Model	Logloss
BiMPM	0.28
XGBoost (Handcrafted)	0.18
Ensemble	0.15

End-to-End Deep Learning Method for Person Search

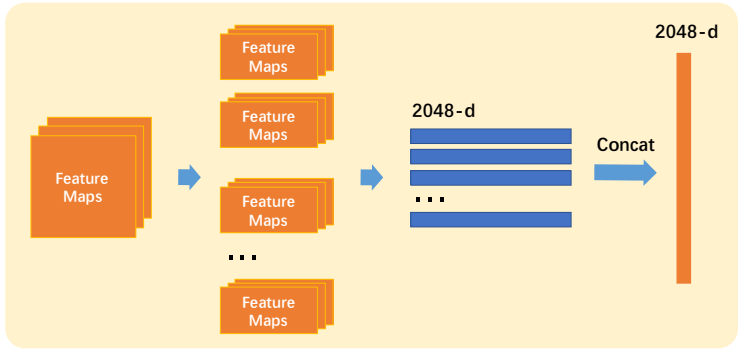
IDEA 1
Local Location Information of Pedestrian

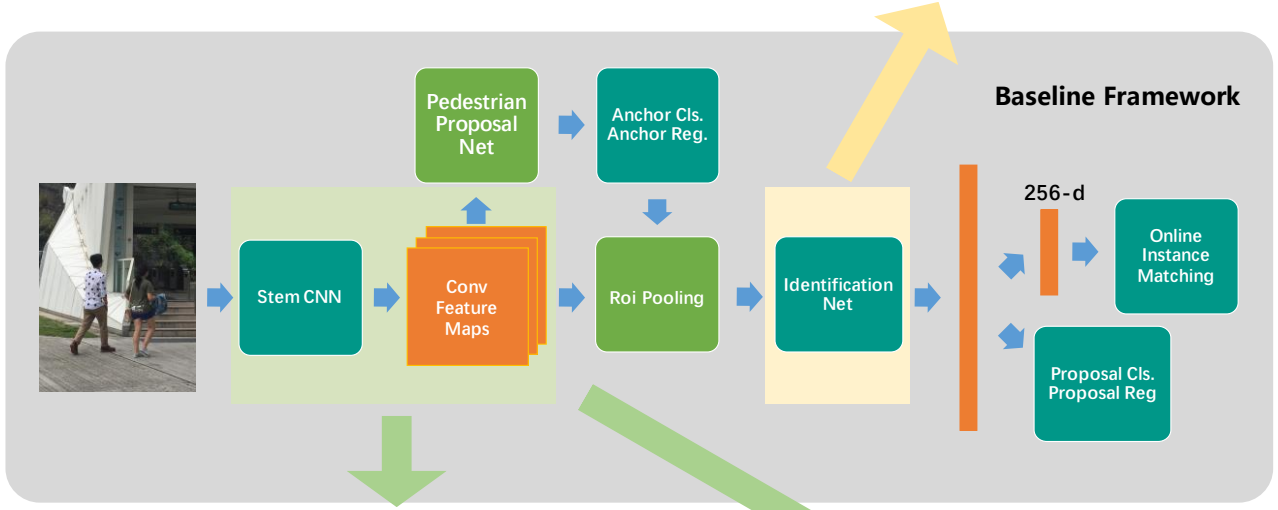


$$f_{final} = \sum_{i}^{n} w_i f_i$$

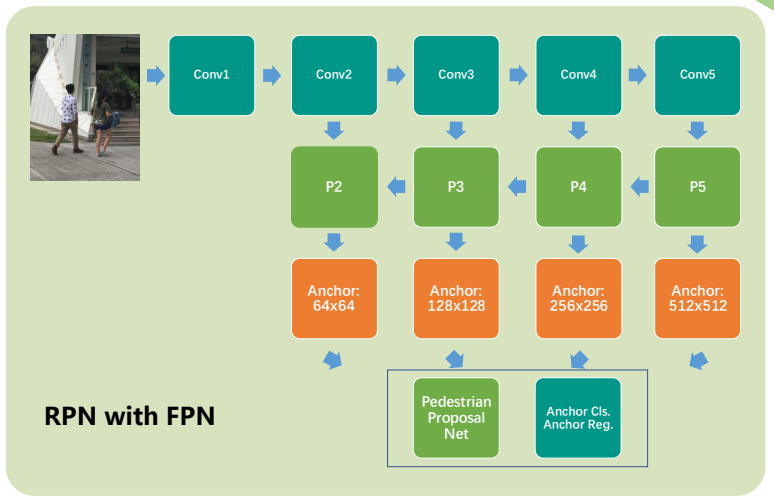
n is the num of parts of person' s body
eg: an image of person can be divided into head, legs, etc.

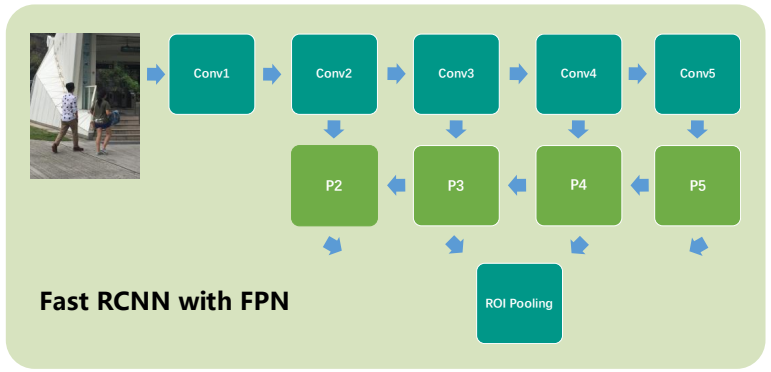
Wi is the weight of part i, which is to be learned with deep network





IDEA2
Feature Map with Feature Pyramid Network (FPN)



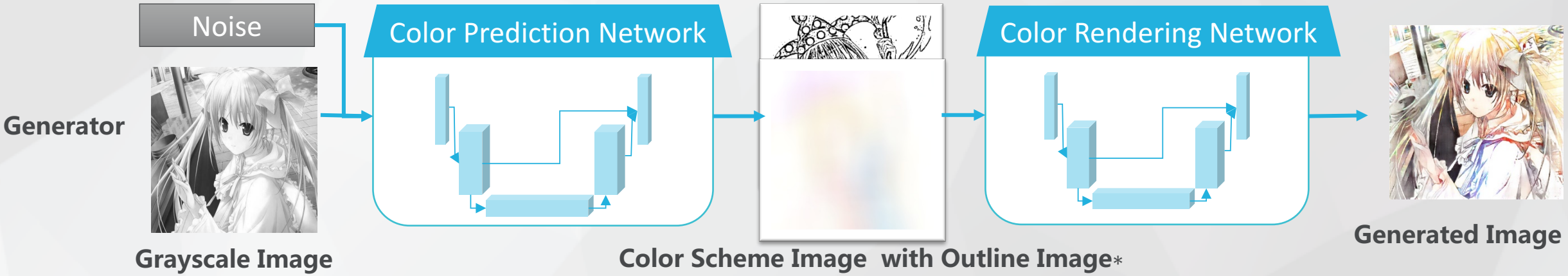


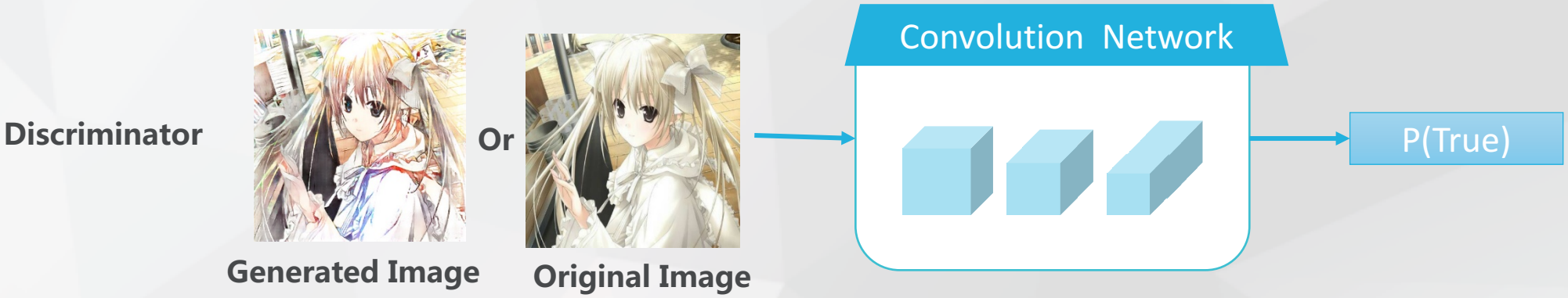
Liufang Sang
slfthuss@gmail.com
Ziru Xu
xzr12thss@gmail.com

School of Software
Tsinghua University

Auto Colorization via Deep Convolutional Adversarial Networks

Goal: Use convoluted network and adversarial network to automatic coloring black and white animated images and produce images close to real.





* Outline Image is computed from origin image by running edge detection algorithm, other than the color prediction network.

Relationship Detection with High-Order Visual Information

Xuefei Ning Xianyu Meng



Fast RCNN

Object pairs

Union

Visual Module:
$V(R_{<i,k,j>}, \Theta | < O_1, O_2 >)$

Language Module :
$f(R_{<i,k,j>}, W) = w_k^T[word2vec(t_i)\ word2vec(t_j)] + b_k$

positions

GBC

score

<dog on bike>



<table next to laptop>



<plant behind clock>

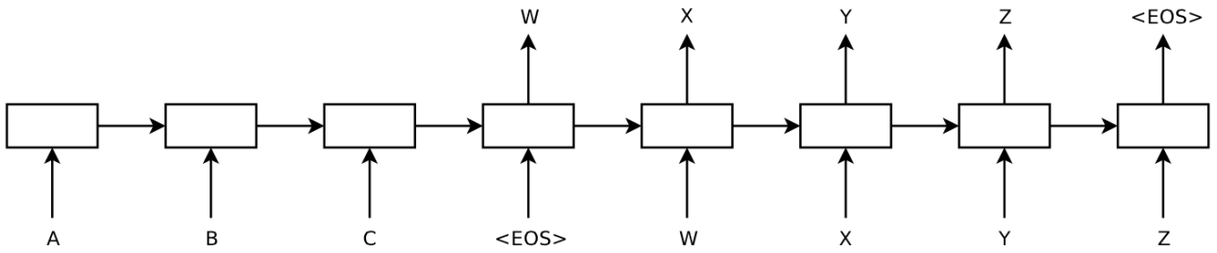


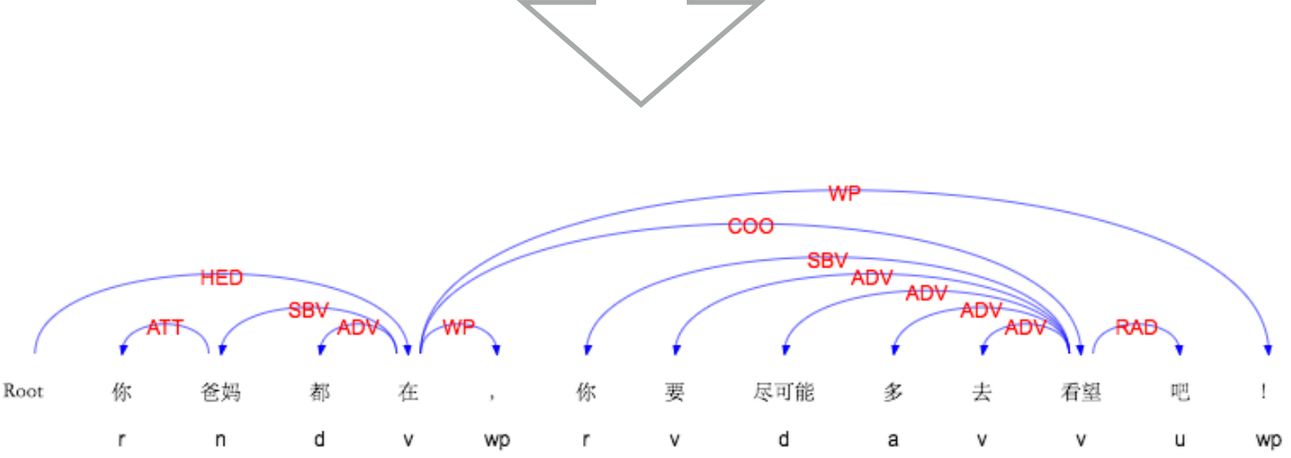
<dog under sky>

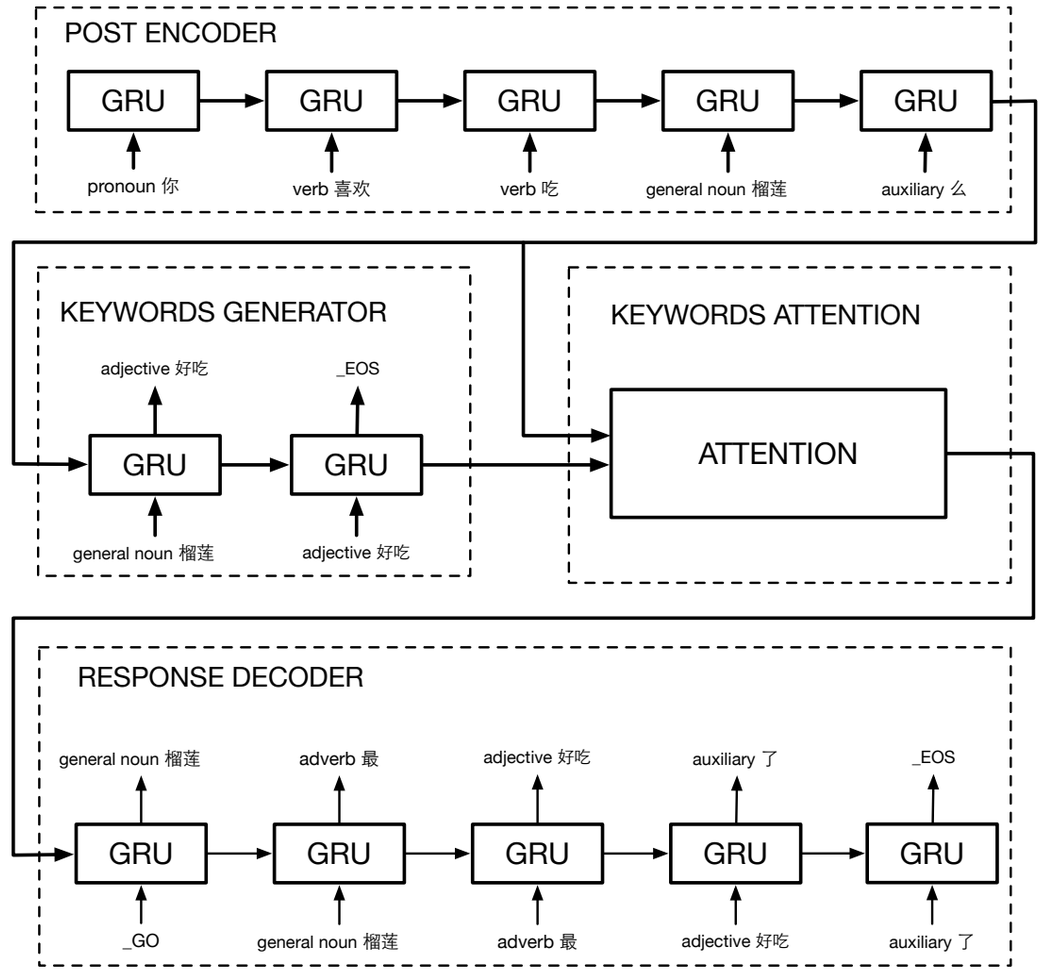


Zero-shot Learning
Top 1 Accuracy

Incorporating Syntactic Knowledge in Natural Language Generation for Dialogue Systems

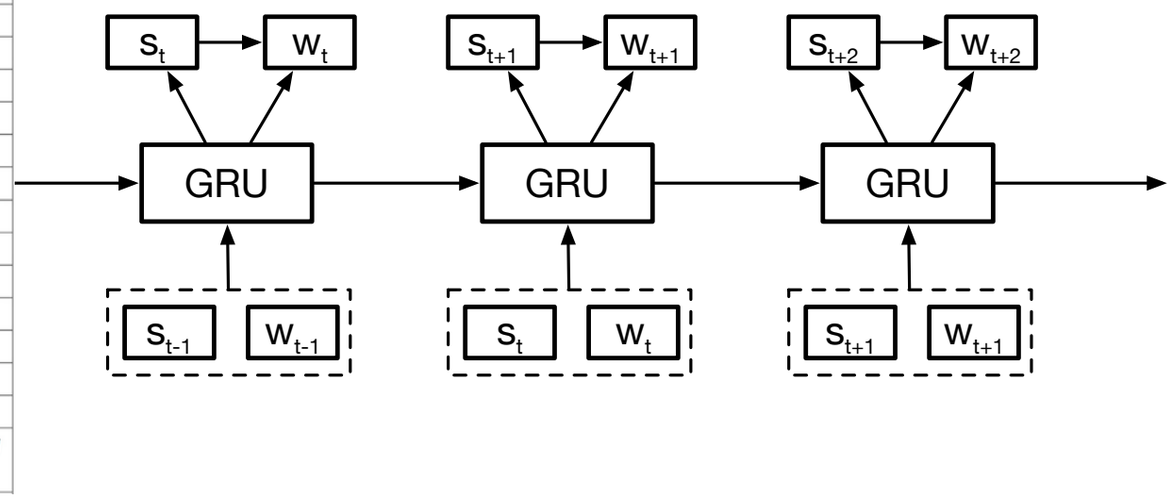






Method	Perplexity
Seq2Seq	23.79
Seq2Seq+encdec	22.84
Seq2Seq+att	21.40
SynSeq	**20.09**

Post	Keywords	Response
你喜欢吃榴莲吗		嗯嗯
	喜欢	喜欢
	是	是的
	喜欢 榴莲	我喜欢榴莲
	喜欢 吃 榴莲	我喜欢吃榴莲
	是 喜欢 吃	是啊，我喜欢吃
	是 喜欢 吃 榴莲	是啊，我喜欢吃榴莲
愿有情人终成眷属！		哈哈
	谢谢	谢谢！
	祝福	祝福你！
	希望	希望如此
	谢谢 祝福	谢谢你的祝福！
	谢谢 祝	谢谢！祝你幸福！
	谢谢 祝福 会	谢谢你的祝福，我会努力的！



KDD CUP 2017

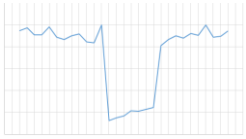
Alibaba Cloud | KDD

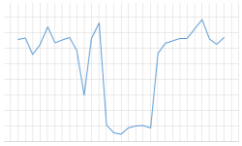
Highway Tollgates Traffic Flow Prediction
Travel Time & Traffic Volume Prediction

曹波 2016210979
费翔 2016310611

Volume Prediction

- sim_mat M to measure the similarity between different days
- exponential function to account for the time window difference in a day and week difference
- A compound similarity function to predict



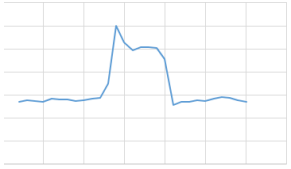


$$\hat{V}_t = \frac{\sum_{i=1}^{H} W(f_i, f_t) \times V_i}{\sum_{i=1}^{H} W(f_i, f_t)}$$

$$W(f_i, f_t) = \rho_1^{H_d} \cdot \rho_2^{W_d} \cdot S_{we(t)we(i)}$$

MAPE: 0.1724

Improvements with more data



- Hierarchical prediction: total volume + portion
- Incorporate the error when getting new data

Travel Time Prediction

$$T_i = \frac{\sum_j sim(t_i, t_j) T_j}{\sum_j sim(t_i, t_j)} \qquad d = \sqrt{\sum (p_i - q_i)^2} \qquad sim(p, q) = \frac{1}{1+d}$$

Base on similarity, assuming that the travel time during 8:00-10:00 of two days are similar if their travel time during 6:00-8:00 are similar

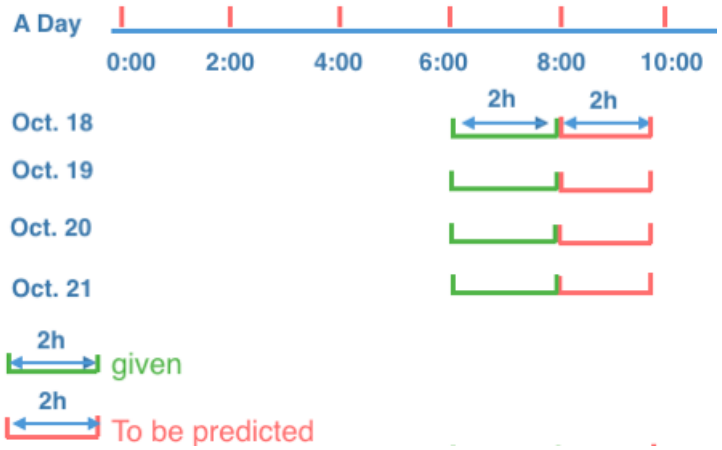
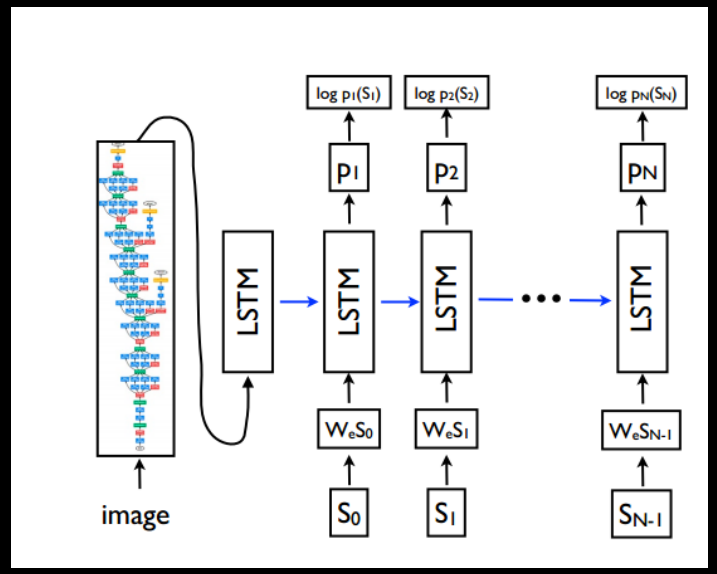




Image Caption in Telling Eye Ground Picture

Luo He, 2016311465, School of Economics and Management, Tsinghua University







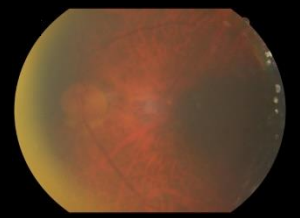
盘沿正常 未见 RNFLD

0) 盘沿 正常 未见 rnfld (p=0.866565)



盘沿上窄 盘沿不正常 盘沿下窄 盘沿不正常 上相应处RNFLD 下相应处RNFLD RNFLD

0) 盘沿 正常 未见 rnfld (p=0.654596)



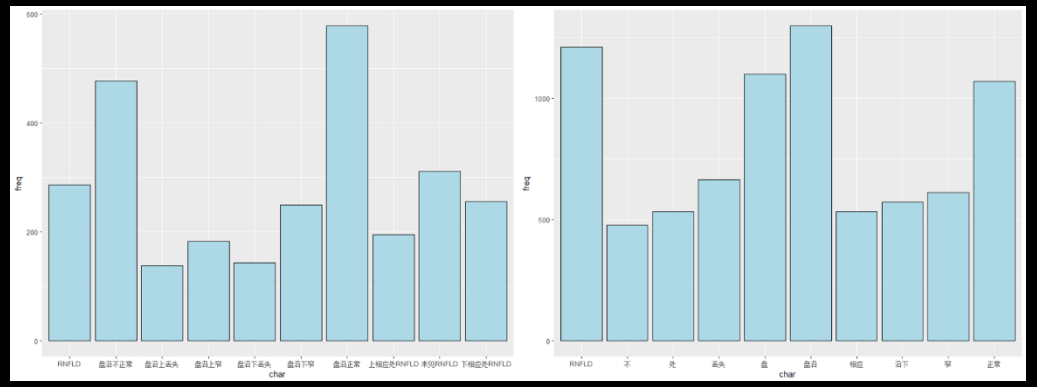
盘沿色淡

0) 盘沿 正常 豹纹 状 眼底 (p=0.479170)

黄斑 灰白 病灶 黄斑 出血

BLEU-4: 0.4919



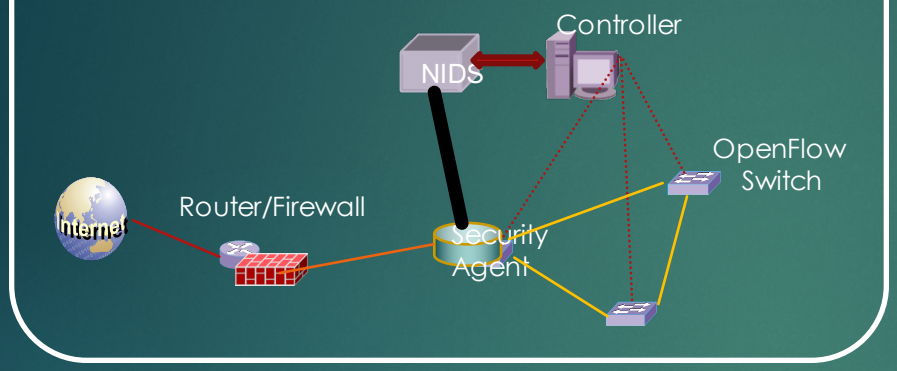


A Deep Learning Approach for Network Intrusion Detection in

Software Defined Networking

Long Qian, Renchuan Zhang
The PLA Information Engineering University

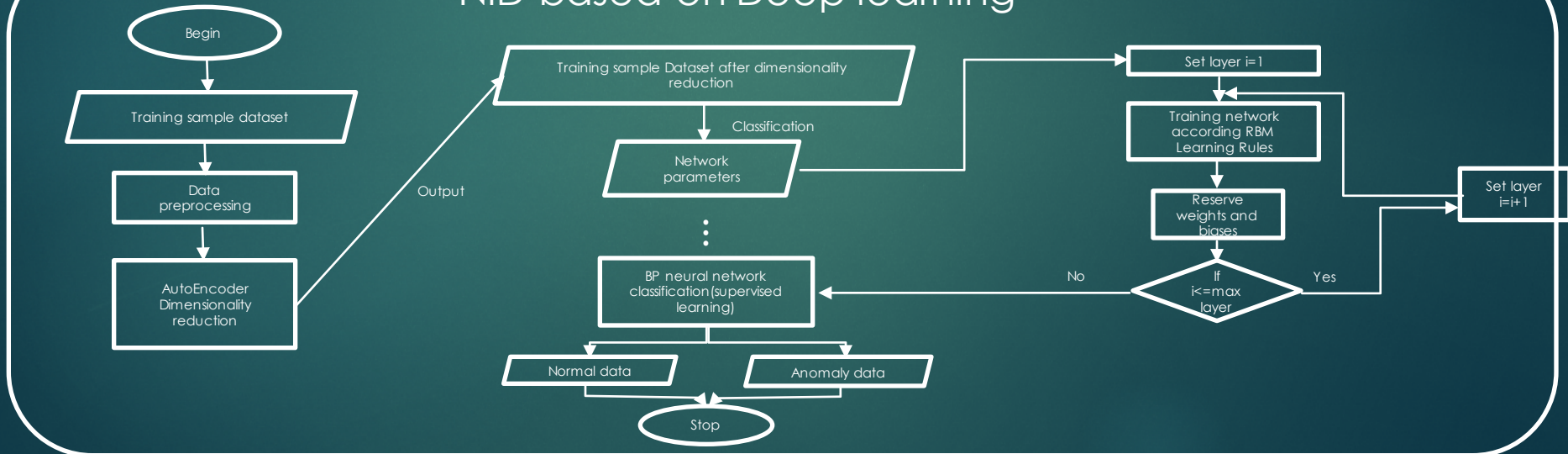
Our System



NSL-KDD Dataset

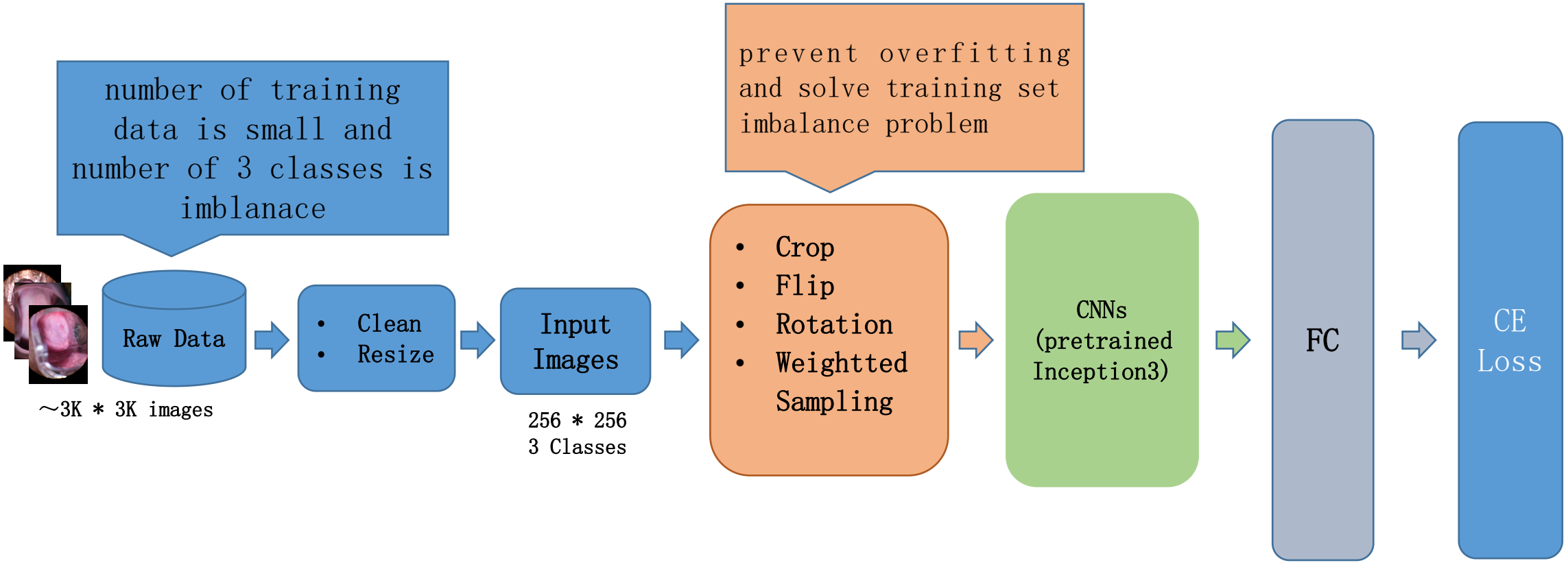
Model	Accuracy	CPU times
DBN	90.5%	2.1s
AE+DBN-5	88.75%	3.5s
AE+DBN-10	92.15%	2.5s

NID based on Deep learning



Intel & MobileODT Cervical Cancer Screening

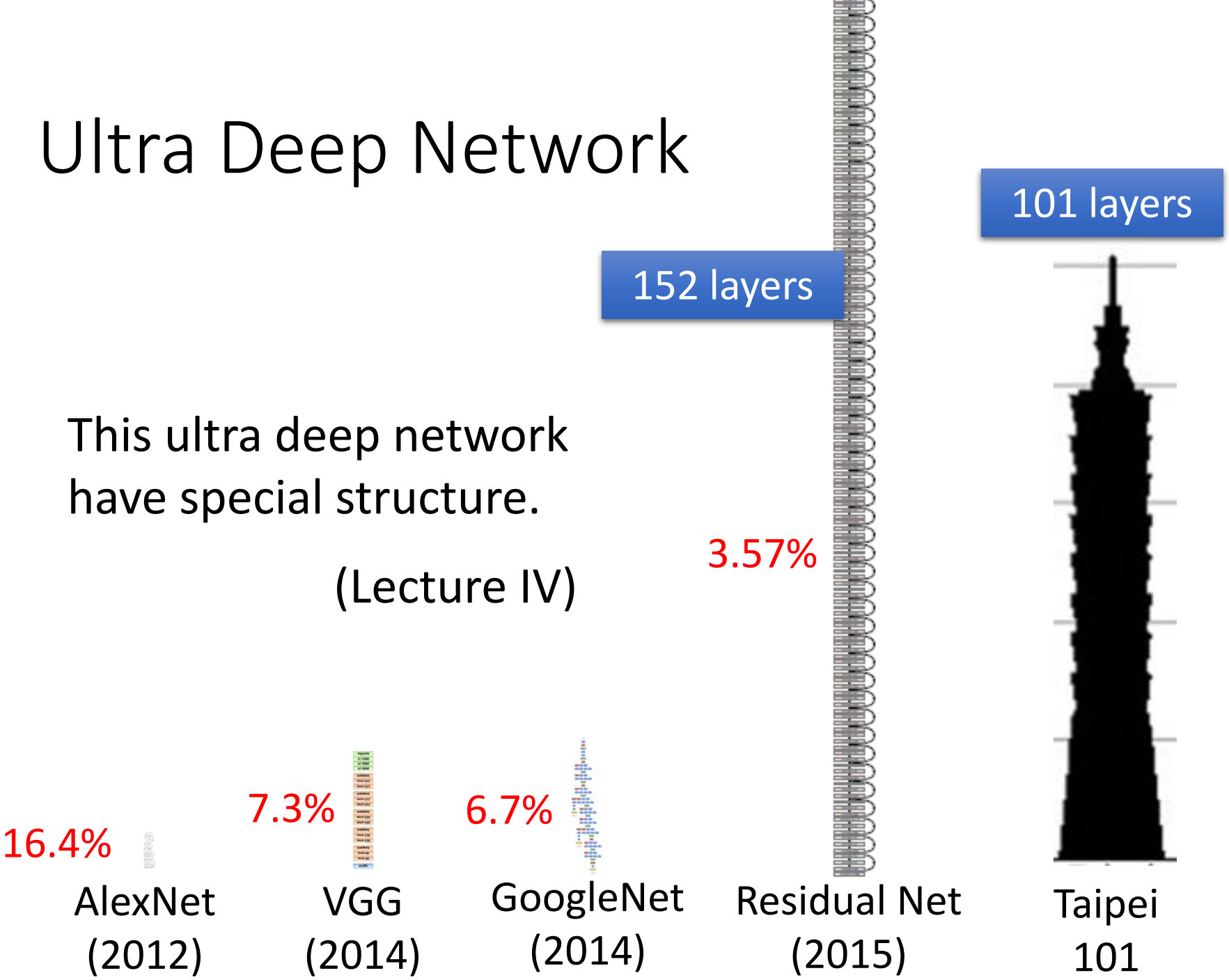
Xia Xin, Wang Gu



Ultra Deep Network

This ultra deep network have special structure.

(Lecture IV)



搜狐图文匹配算法大赛

张家伟 P16206013

