[2021 Spring] Principles of Deep Learning Project

Twitter Recommendation System – Recsys challenge 2021

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Introduction: about competition

Competition objective
The **'real-world task'** of tweet engagement prediction **'in a dynamic environment'**.
※ **tweet engagement prediction**: Like, Retweet, Quote, and replies

Constraints
- **Latency** constraints (numerous dataset size)
- Satisfy **multi-goal optimization**, accuracy and fairness
- Targets are **divided as 5 groups per popularity for scoring fairness**

Problem Definition
Predict **0(non-interact)** or **1(interact)** label of different engagement type **(Binary Classification)**

Metric

- **Average Precision Score – Accuracy**

$$AP = \sum_{n} (R_n - R_{n-1}) P_n$$

- **Relative Cross Entropy(RCE) – Fairness**

$$RCE = \frac{CE_{naive} - CE_{pred}}{CE_{naive}} * 100$$

Introduction: dataset

Dataset served as Twitter APIs

- Train data is **259 numbers of TSV files** which have **3 million rows and 800MB** per one file
- It is **closed to 1 billion** data points
- Dataset **split as train and valid dataset by number of weeks** per a month
  ※ Week 1-3: train / Week 4: valid

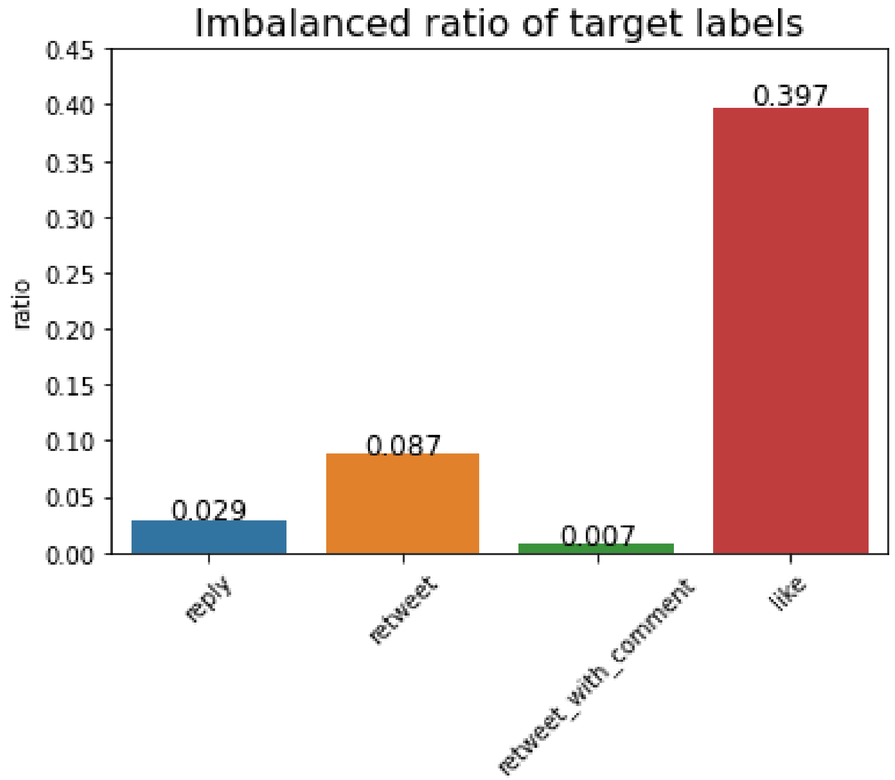
Columns of Dataset

Items	Names
Features	"text_ tokens", "hashtags", "tweet_id", "present_media", "present_links", "present_domains","tweet_type","language", "tweet_timestamp", "engaged_with_user_id", "engaged_with_user_follower_count", "engaged_with_user_following_count", "engaged_with_user_is_verified", "engaged_with_user_account_creation","enaging_user_id", "enaging_user_follower_count", "enaging_user_following_count", "enaging_user_is_verified“,"enaging_user_account_creation", "engagee_follows_engager"
Labels	"reply_timestamp", "retweet_timestamp", "retweet_with_comment_timestamp", "like_timestamp"

Introduction: Restrictions

Dataset suffered imbalance at all of labels

- Among them, 3 labels have severe imbalance ("reply_timestamp", "retweet_timestamp", "retweet_with_comment_timestamp")



Submission Environment

- e2-highmem-16 on GCP with 64GB memory
- 24 hours time limit
- Test dataset ~ 10 million rows

Machine Name	vCPUs[1]	Memory (GB)	Max number of persistent disks (PDs)[2]	Max total PD size (TB)	Local SSD	Maximum egress bandwidth (Gbps)[3]
e2-highmem-2	2	16	128	257	No	4
e2-highmem-4	4	32	128	257	No	8
e2-highmem-8	8	64	128	257	No	16
e2-highmem-16	16	128	128	257	No	16

Methodologies: text token

Text token is tokenized text of target tweet post

For utilizing token, it needs to be converted as arbitrary feature by some methods.

There are methodologies adopted below:

	tweet_id	text_ tokens
0	D6621E1038904DA83CBBA1DE9F4FFA7A	101 56898 137 14657 11462 11460 66730 131 1139...
1	1F0C624B6B3455AA8C14A7C4EF6B342E	101 56898 137 52544 10147 12396 11233 11975 13...
2	F944E479EBDEEECBFBA03F47D8B5B79A	101 56991 216 216 19318 11301 14120 131 120 12...
3	0F98BD50C159E189E7F6F8203227FC36	101 56898 137 18087 11205 11090 11010 10269 13...
4	3C1A2B662FBA0436DCBCCD488B08E2D4	101 56898 137 12882 31604 10291 89525 11359 11...

Method	Model type	Output
TFIDF-GloVe	Unsupervised	d dimension vector
SIF(Embedding by GloVe)	Unsupervised	d dimension vector
DAN(Deep Average Network)	Supervised	d dimension vector
DEC(Deep Embedded Clustering)	Unsupervised	n clustered integer

Methodologies: vectorizing by GloVe[1]

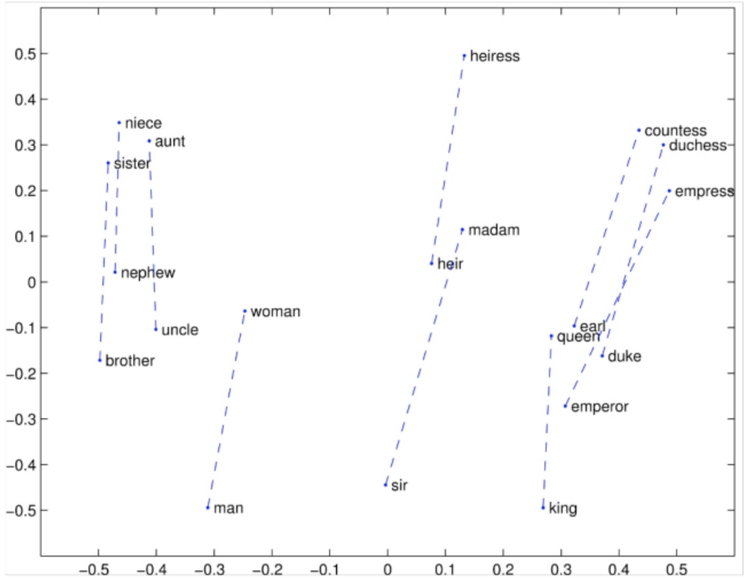
There is word embedding as background of implementation

GloVe model selected

It emerged for covering drawback of LSA and Word2Vec model
- LSA(Latent Semantic Analysis): weakness at analogy task
- Word2Vec: weakness of locality from window

It adopts Co-occurrence Probability made from Co-occurrence matrix

The objective is finding function F given three target vector like below:



$$F(w_i, w_j, \tilde{w}_k) = \frac{P_{ik}}{P_{jk}}$$

Probability and Ratio	$k = solid$	$k = gas$	$k = water$	$k = fashion$
$P(k\|ice)$	1.9×10^{-4}	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
$P(k\|steam)$	2.2×10^{-5}	7.8×10^{-4}	2.2×10^{-3}	1.8×10^{-5}
$P(k\|ice)/P(k\|steam)$	8.9	8.5×10^{-2}	1.36	0.96

Methodologies: weighted average (tfidf-GloVe, SIF[2])

The simplest implementation is to take averages about all vectors of sentence

However, it could be lost some sense of important word by concatenating

Then, try “Weighted Average” by tf-idf or SIF(SIMPLE BUT TOUGH-TO-BEAT) method

$$TF-IDF = tf(d,t) * idf(t)$$
$$= tf(d,t) * log(\frac{n}{df(t)})$$

- $tf(d,t)$ number of counts the word t appeared in specific document d,
- $df(t)$ inverse of number of counts the word t appeared in whole documents

TF-IDF formula

Algorithm 1 Sentence Embedding

Input: Word embeddings $\{v_w : w \in \mathcal{V}\}$, a set of sentences $\mathcal{S}$, parameter a and estimated probabilities $\{p(w) : w \in \mathcal{V}\}$ of the words.
Output: Sentence embeddings $\{v_s : s \in \mathcal{S}\}$

1: **for all** sentence s in $\mathcal{S}$ **do**
2: $v_s \leftarrow \frac{1}{|s|} \sum_{w \in s} \frac{a}{a+p(w)} v_w$
3: **end for**
4: Form a matrix X whose columns are $\{v_s : s \in \mathcal{S}\}$, and let u be its first singular vector
5: **for all** sentence s in $\mathcal{S}$ **do**
6: $v_s \leftarrow v_s - uu^\top v_s$
7: **end for**

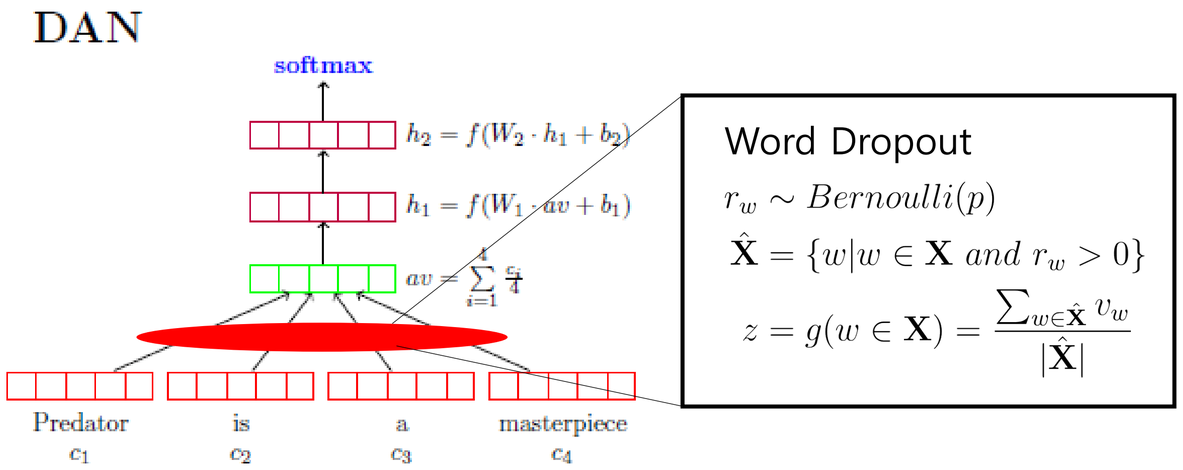
SIF Pseudo Code

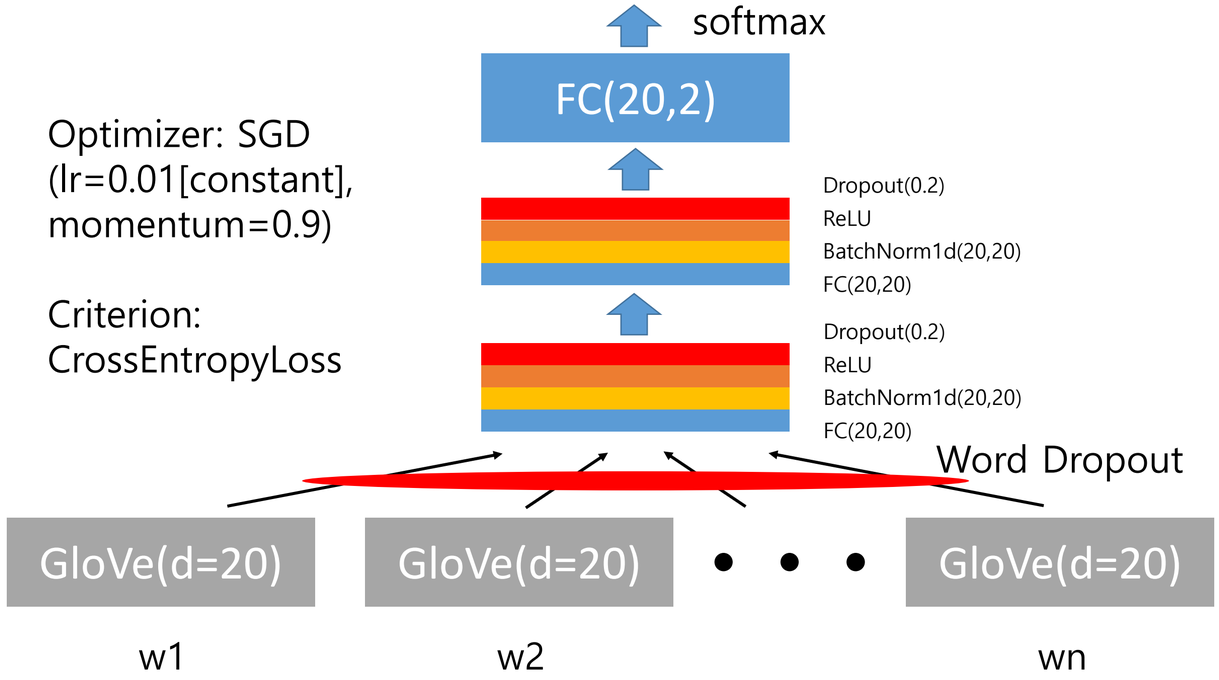
Methodologies: DAN (Deep Averaging Network[3])

For comparing with unsupervised average method, DAN(Deep Average Network) used

DAN is learned by 2 fully connected layer using averaged word vector input values

To prevent overfitting, word dropout utilized before averaging word embeddings



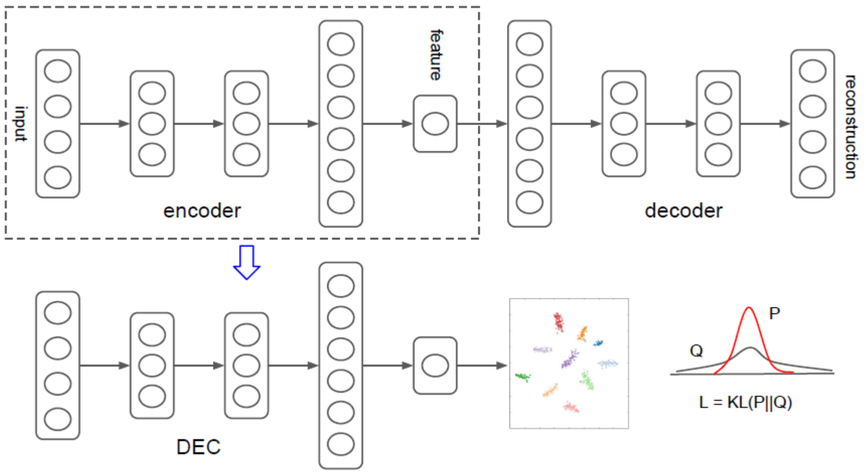


Methodologies: DEC (Deep Embedded Clustering[4])

Unlike vectorization method, another method is utilizing clustered feature

For this, DEC(Deep Embedded Clustering) which allocates cluster by pretrained encoder

It proceeded 2 phases greedy layer wised pretrain and improve clustering by pretrained encoder



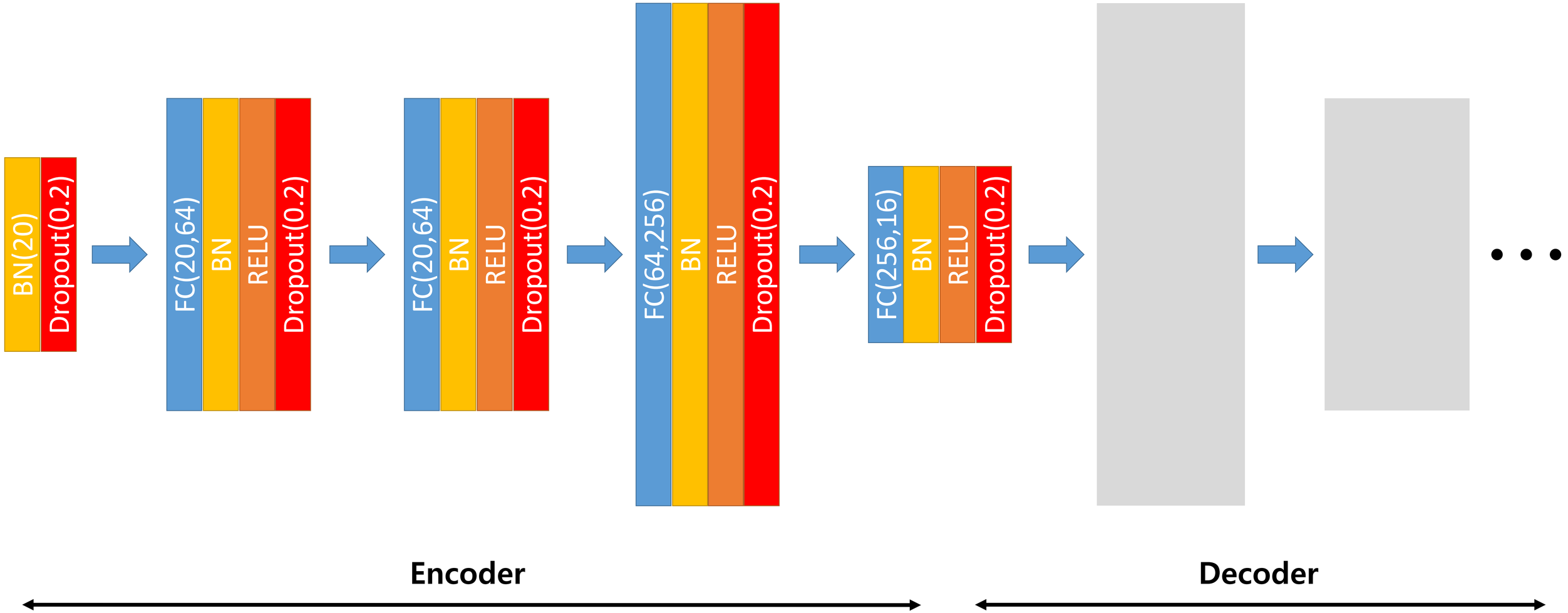
Soft Assignment

$$q_{ij} = \frac{(1 + ||z_i - \mu_j||^2/\alpha)^{-\frac{\alpha+1}{2}}}{\sum_{j'}(1 + ||z_i - \mu_{j'}||^2/\alpha)^{-\frac{\alpha+1}{2}}}$$

Iteratively refine cluster by KL Divergence Minimization

$$L = KL(P||Q) = \sum_i \sum_j p_{ij} log \frac{p_{ij}}{q_{ij}}$$

Methodologies: DEC (Deep Embedded Clustering[4])



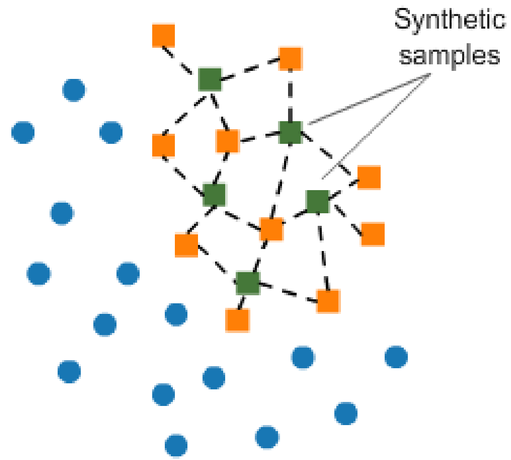
Methodology：Generative Adversarial Network for Data Imbalance

Extremely imbalanced data[5]

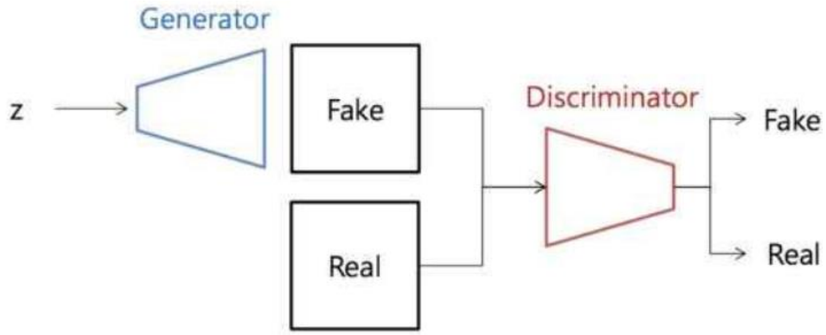
Re-extraction：It's simple, but Overfitting happens

SMOTE : Overfitting mitigates, but generates potential noise data

GAN : Troubleshooting Potential Noise Data Generation



SMOTE



GAN

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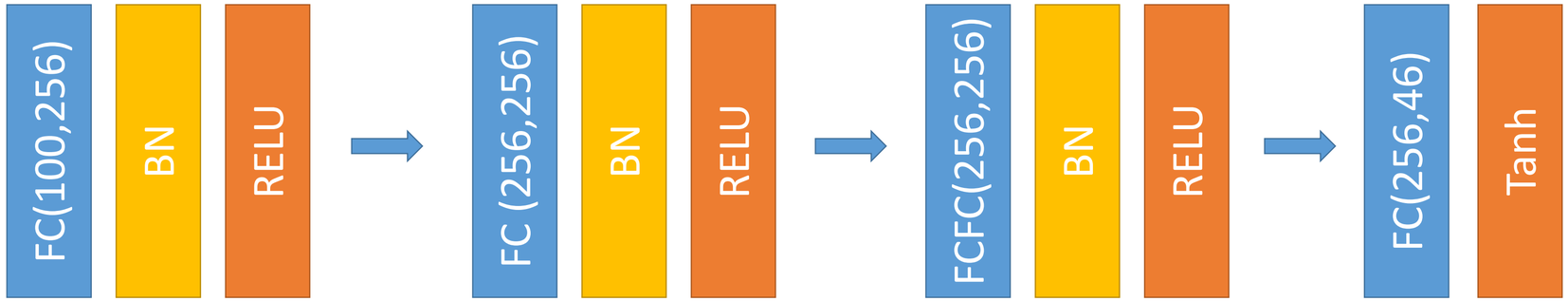
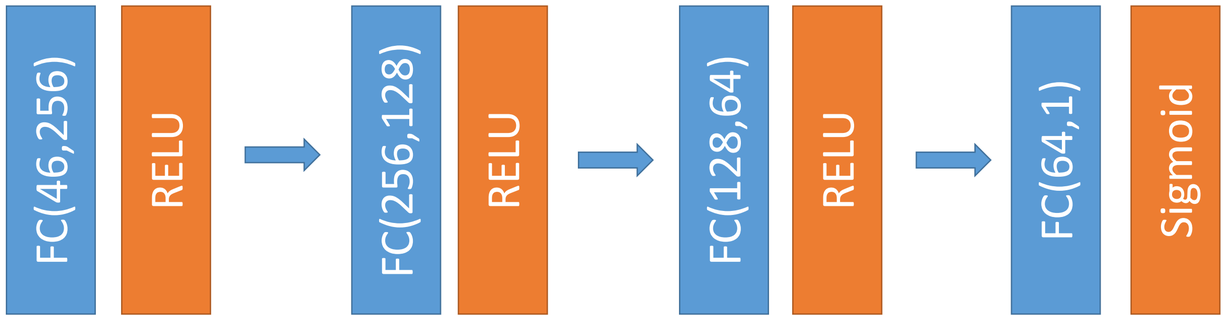
Methodology：Generative Adversarial Network for Data Imbalance



Generator Model



Discriminator Model

Criterion : BCELoss
Optimizer : Adam

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Methodology : Classification model - ANN

Binary classification

Decision Tree 2:17 Neural Network

Multiclass classification

Decision Tree 0:7 Neural Network

Regression

Decision Tree 4:12 Neural Network

Compared on OpenML datasets[6]

It performs better than other machine learning models

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Methodology : ANN

Continuous variable : engaged_with_user_following_count, engaged_with_user_follower_count, engaging_user_follower_count, engaging_user_following_count, engaged_time - engaging_time tweet_time - engaging_time, tweet_hour, language(Rank), num_GIF, num_Video, num_Photo, engaged_time, engaging_time, tweet_timestamp, ratio_enaging_follow, ratio_enagaged_follow

-> **RobustScaler scaler**

Discrete variable(Dummy variable) : tweet_type_0, … ,tweet_type_3, engaged_with_user_is_verified, engaging_user_is_verified, engagee_follows_engager, present_links, bool_(engaged_time > engaging_time)

Text variable (SIF, TFIDF, DAN) : sentenc_vector_0, … , sentenc_vector_19, cluseter

Input data has 46 features

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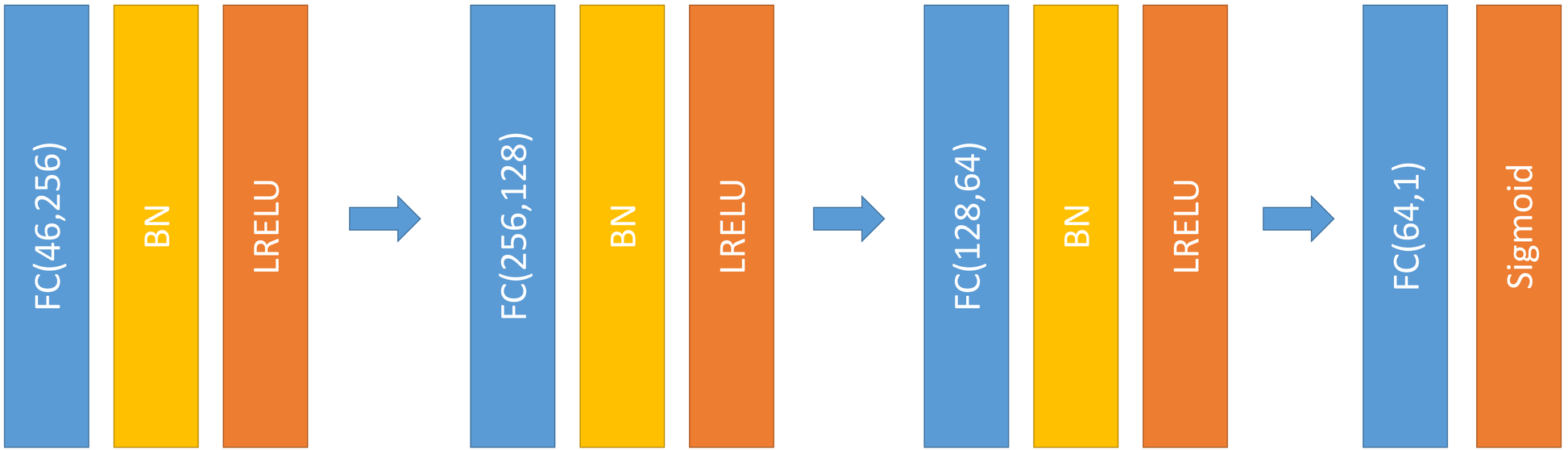
Methodology : ANN



ANN Model

Criterion : SmoothL1Loss
Optimizer : Adam

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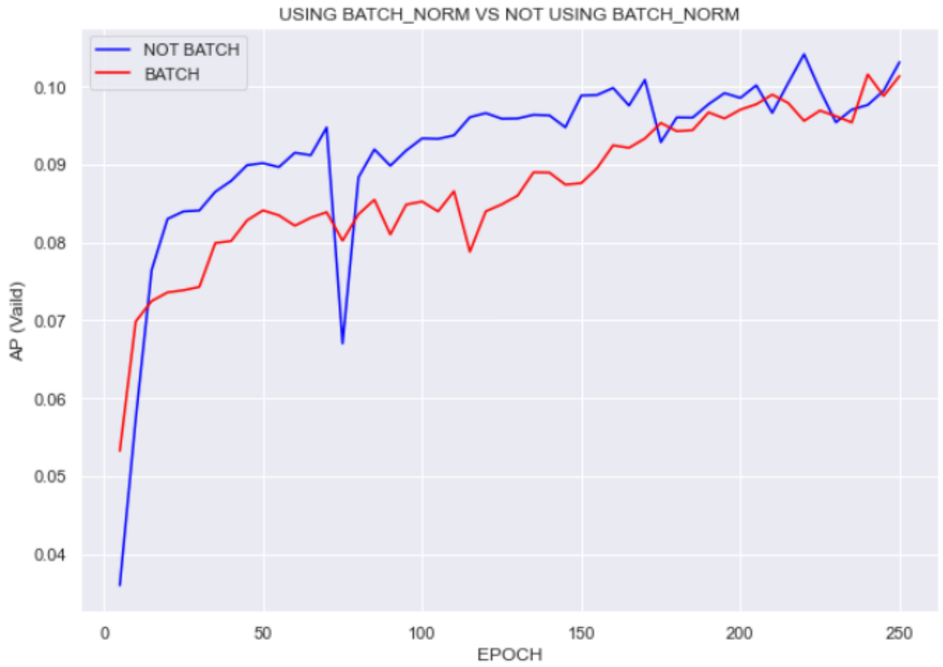
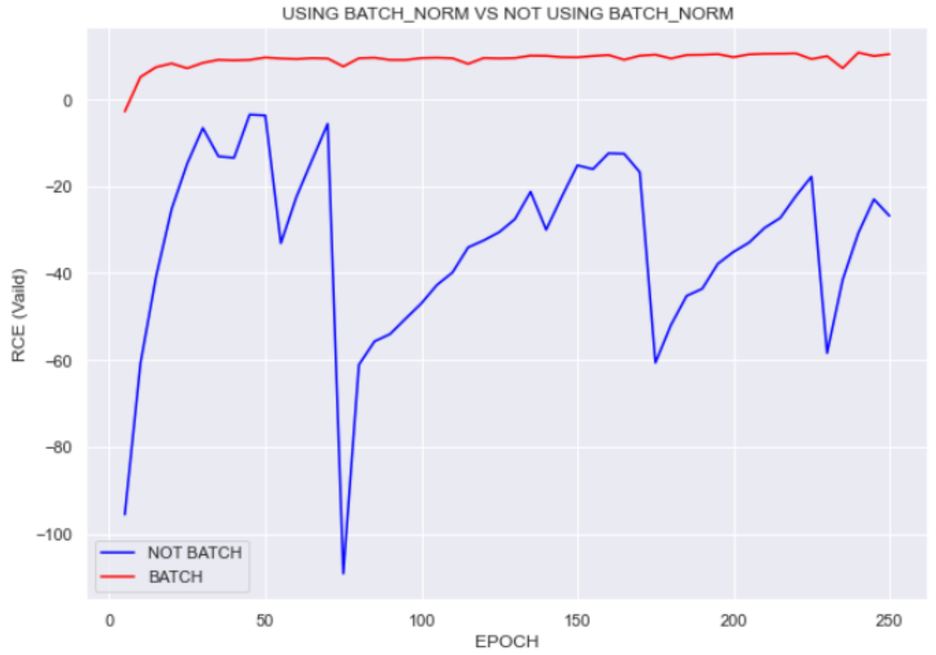
Experiments

Valid Set: **Extract 50% randomly from Test Data**

Experiments : Batch Normalization (Not Using Text token)





Baseline Model : **Using Batch Normalization**

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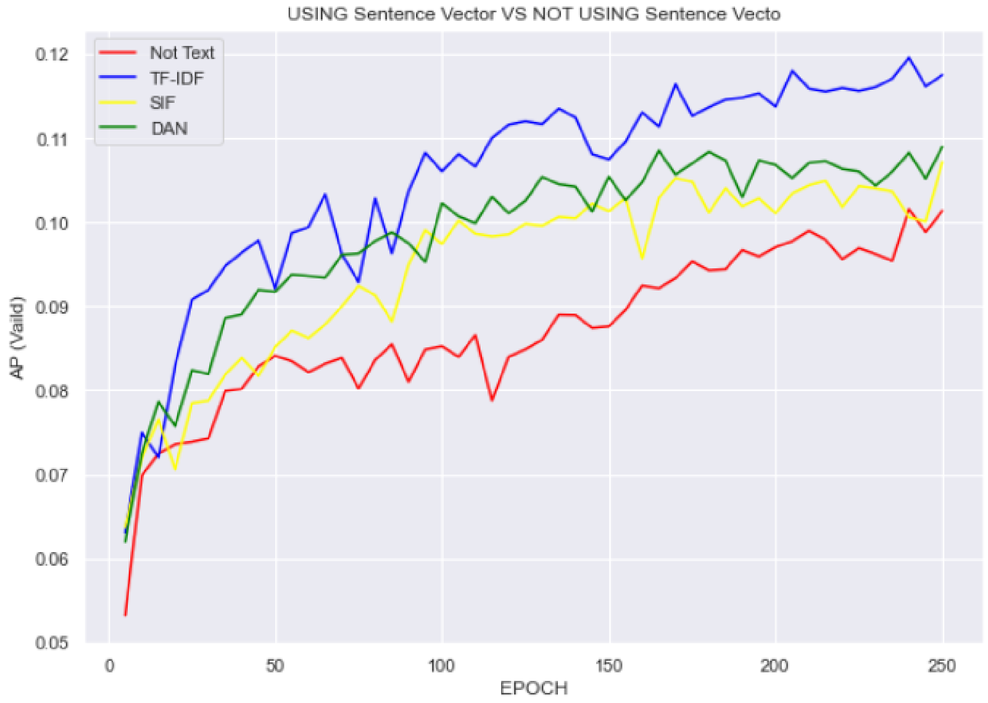
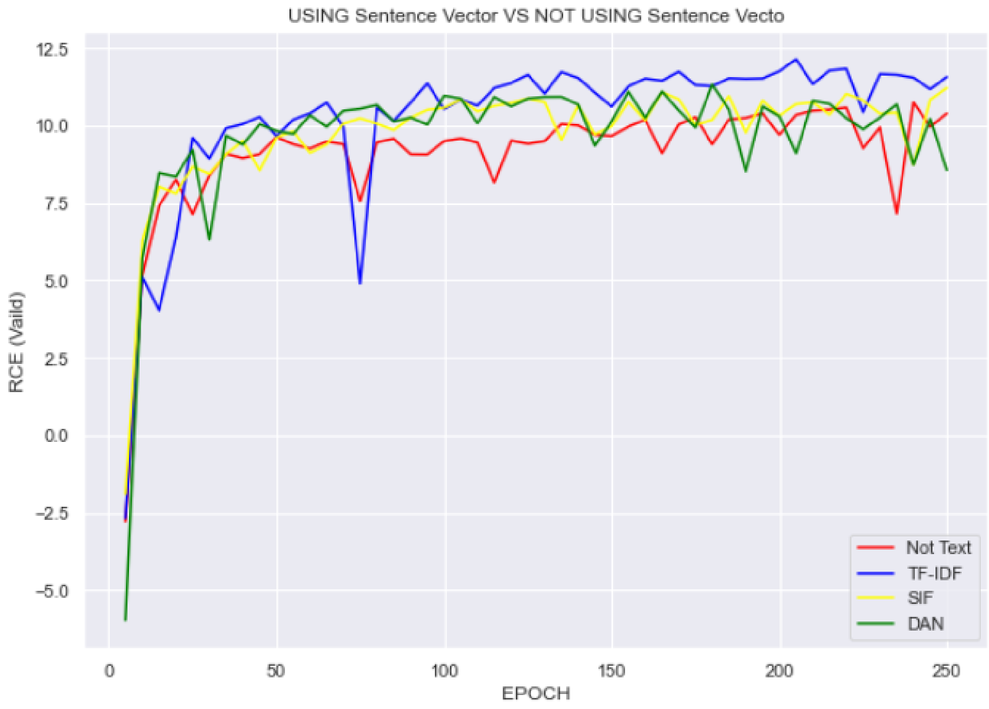
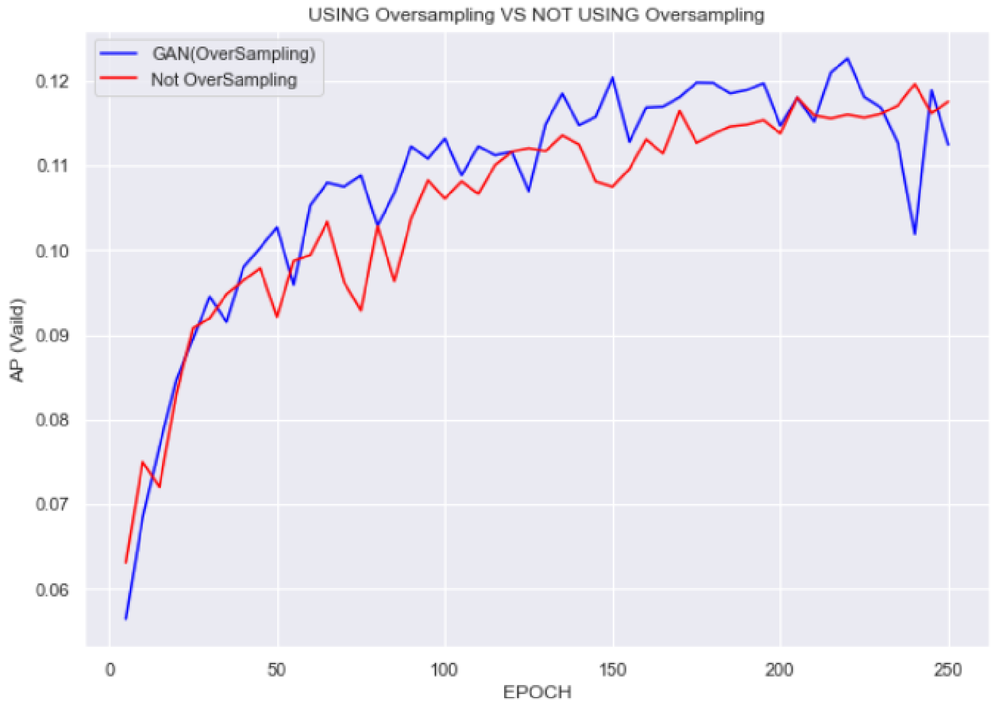
Experiments : Sentence Vector

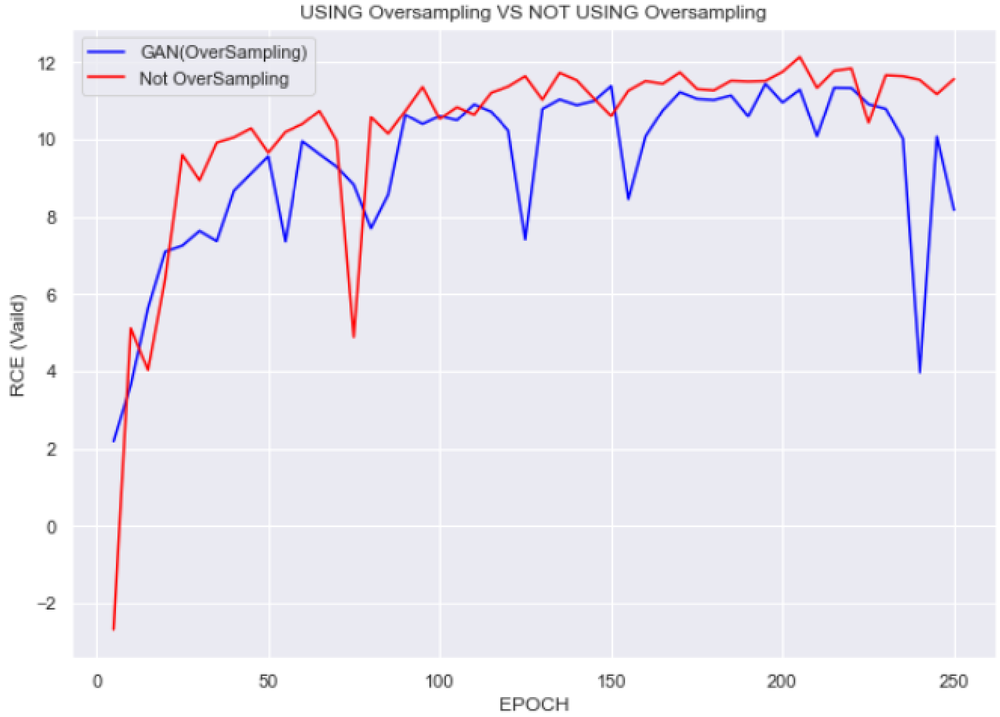




Baseline Sentence Vector : **tfidf-GloVe**

Experiments : OverSampling (GAN)





Experiment

Batch Norm	Sentence	GAN	AP	RCE
X	X	X	0.104171	-3.5193
O	X	X	0.10158	10.7507
O	SIF	X	0.10718	11.2185
O	DAN	X	0.10898	11.3233
O	tfidf-GloVe	X	0.11961	12.1408
O	tfidf-GloVe	O	0.12263	11.4452

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Conclusion

1. Text is important to followers on Twitter
   (Approximately 20% increase in performance **(tfidf-GloVe)**)
   -> Followers read and sympathize

2. Batch normalization is more effective for **RCE** than **AP**
   -> Batch normalization is over performing the naive prediction[7]

3. **GAN** is more effective for **AP** than **RCE**

4. Model will **be split for 5 groups by popularity** for enhancing **RCE** further

To increase **RCE**, we are going to create a model that takes into account followers numbers.

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THANK YOU