

# YouTube View Count Prediction

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# Background

## Existing Work

Prediction of future view counts of a specific YouTuber's uploaded videos

Prediction of view counts utilizing numerical features (meta)

Study on feature importance of thumbnail and meta-level features

## Problems of Existing Work

Limited to certain YouTuber

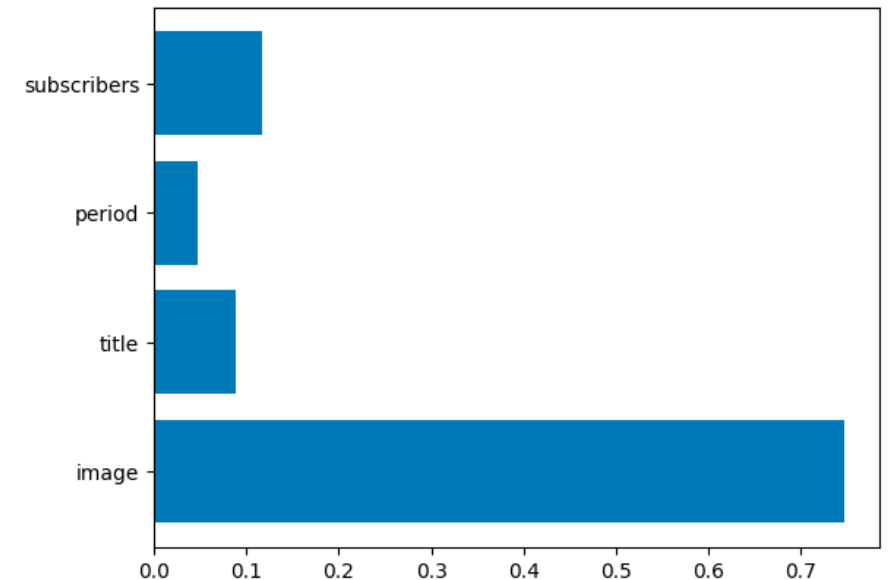
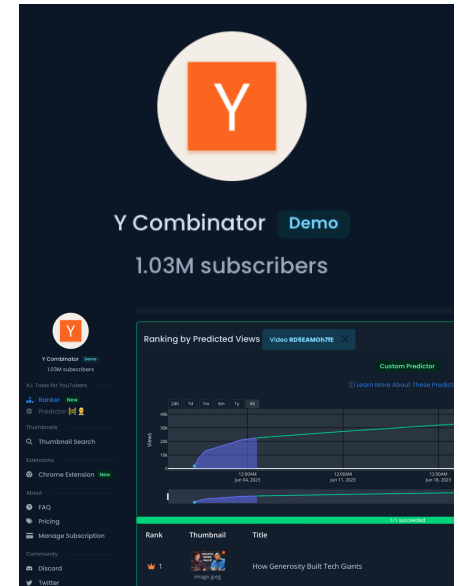
No help in deciding thumbnail or title

Not utilizing thumbnail features

## Feature Importance

Use XGBoost to measure

how much the corresponding feature affects prediction



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## Contribution

## Our Goal

Predict the view counts of a YouTube Mukbang video utilizing thumbnail features

## Main Contribution

Crawled and used our own dataset to solve the problem

Designed an optimal architecture to utilize features in balance including thumbnail features.

Successfully predict view counts of a YouTube mukbang video prior to upload

## HTTPSnet

Hierarchical prediction model with Thumbnail, Title, Period and Subscribers

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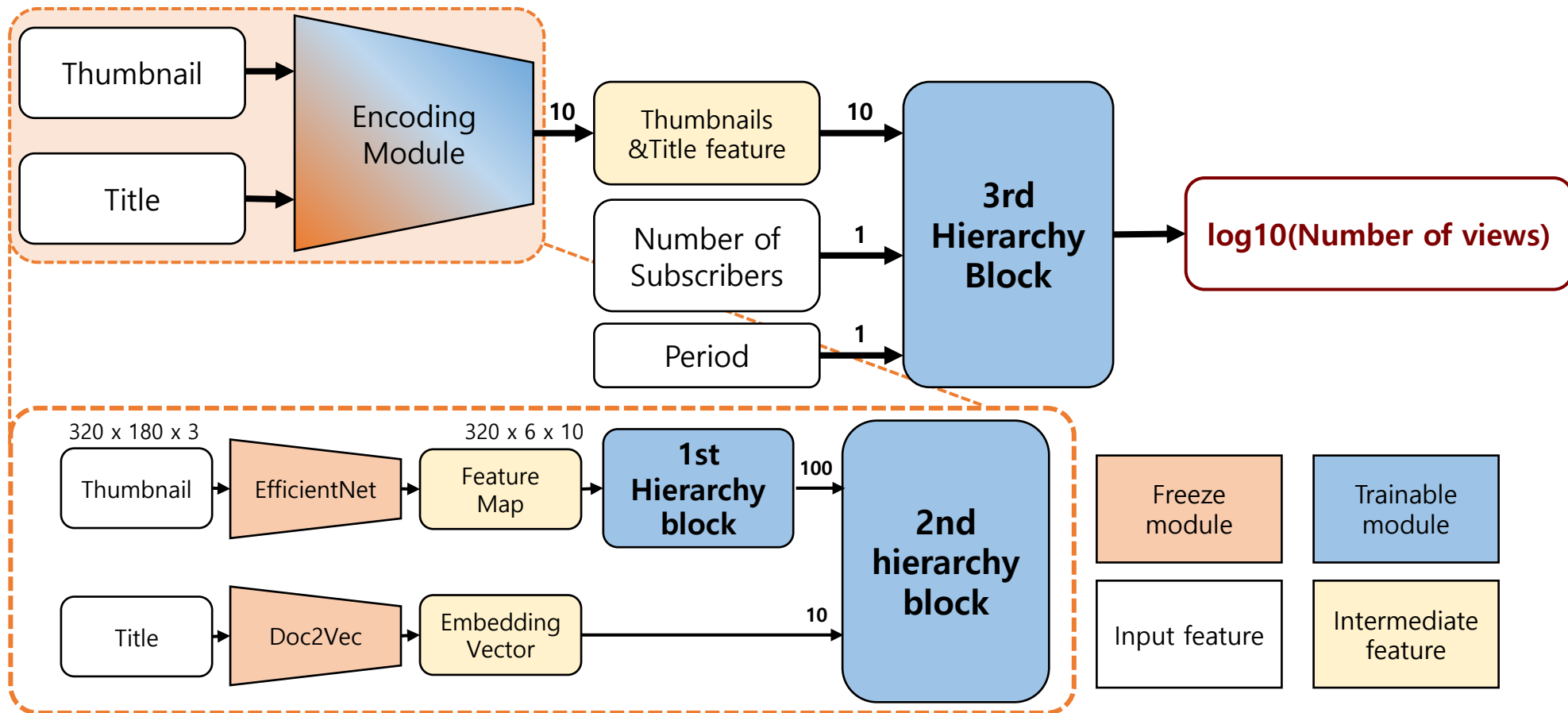
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## Model Design

## Overall architecture of our HTTPSnet

We designed **hierarchical architecture** model for view count prediction

**EfficientNet** and **Doc2Vec** are utilized for **representing thumbnail and title as a vector**





## Why hierarchical architecture?

There is a serious imbalance in the size of the input vectors.

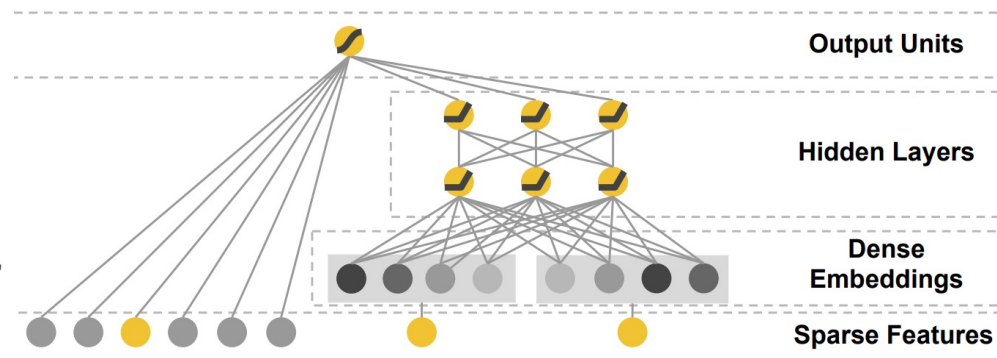
Input type	Shape of vector
Thumbnail	(320,6,10)
Title	(10,1)
Upload period	(1,1)
Number of subscribers	(1,1)

Too large image vector can make other input vectors become faint

## Wide & Deep Learning for Recommender Systems

Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, Rohan Anil, Zakaria Haque, Lichan Hong, Vihan Jain, Xiaobing Liu, Hemal Shah

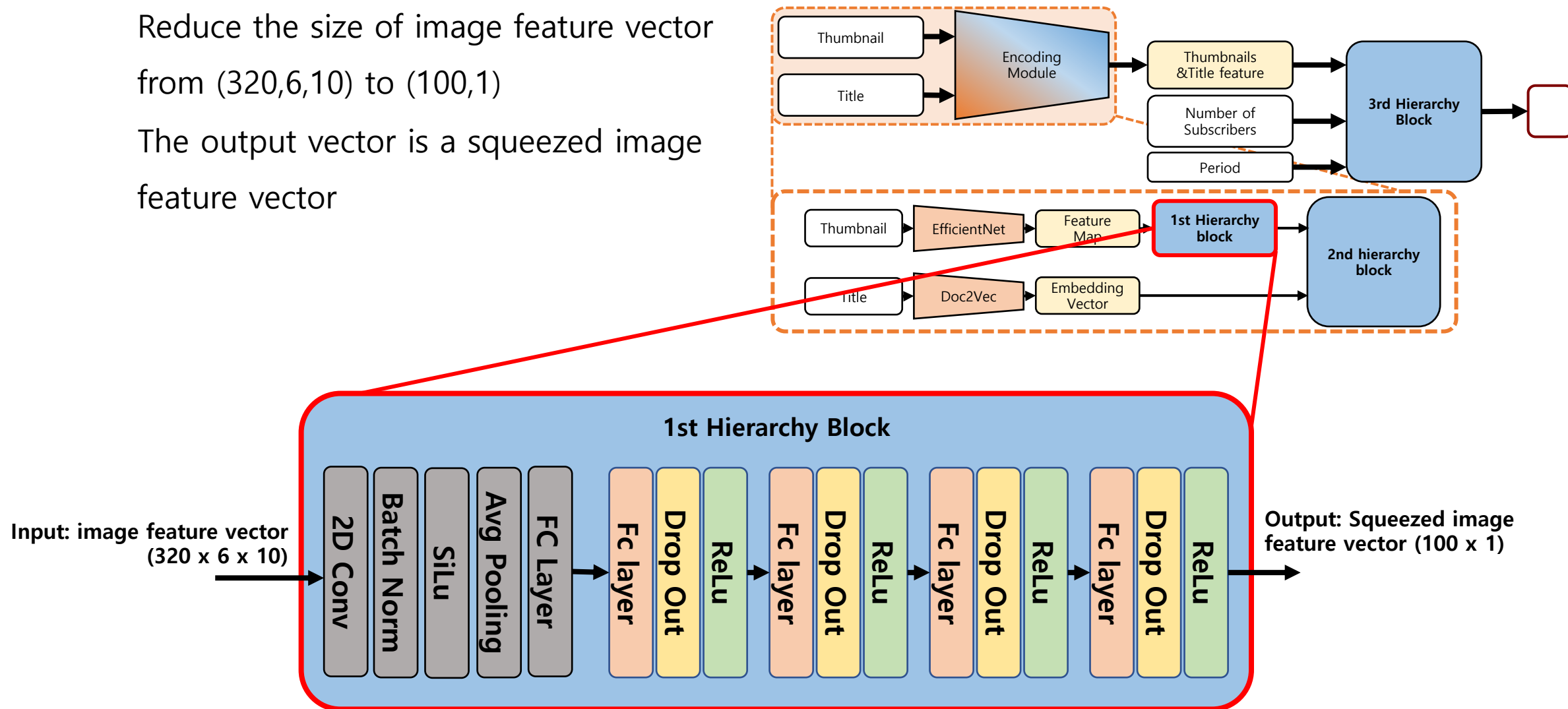
Google Inc.\*



## 1<sup>st</sup> Hierarchy Block

Reduce the size of image feature vector from (320,6,10) to (100,1)

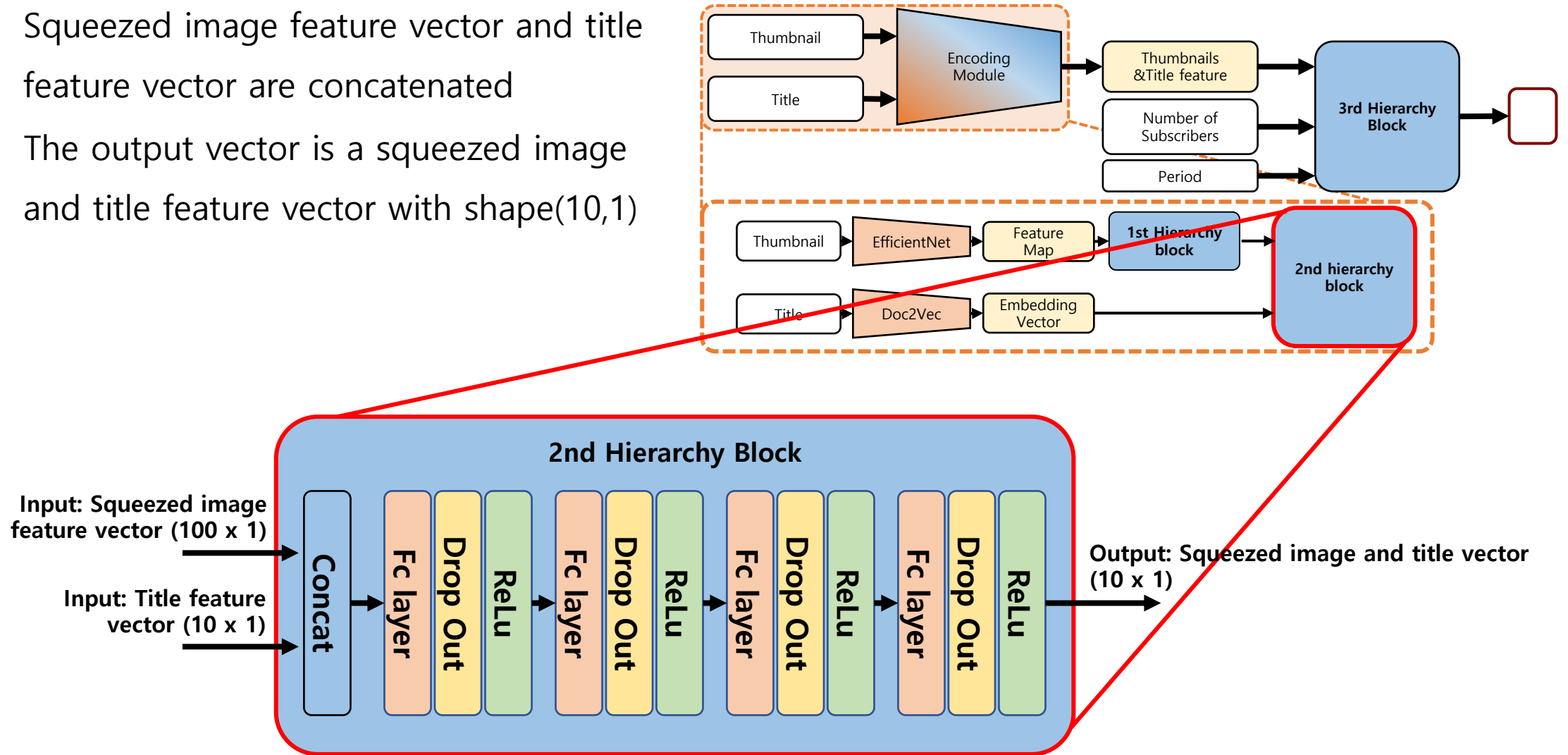
The output vector is a squeezed image feature vector



## 2<sup>nd</sup> Hierarchy Block

Squeezed image feature vector and title feature vector are concatenated

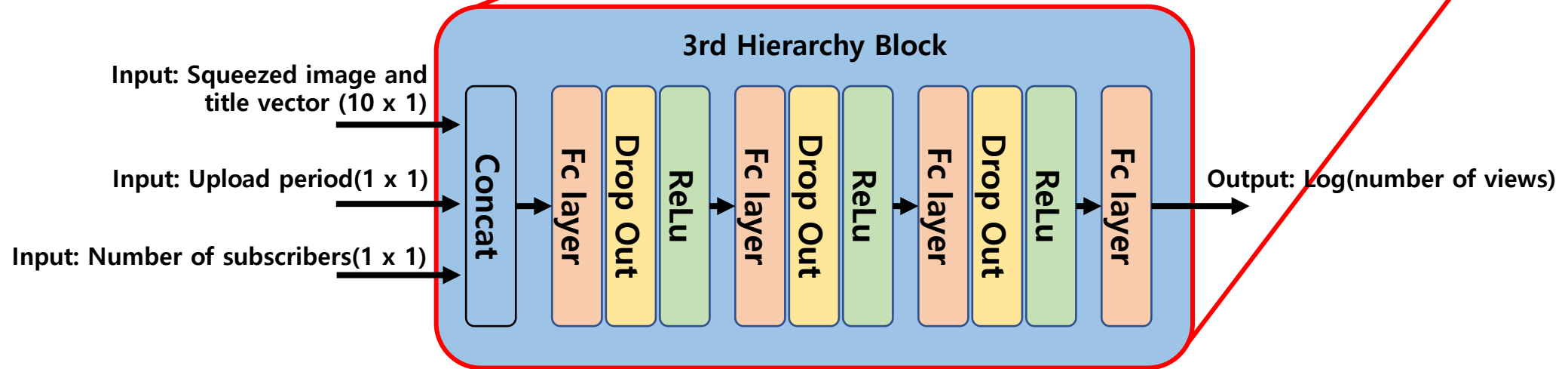
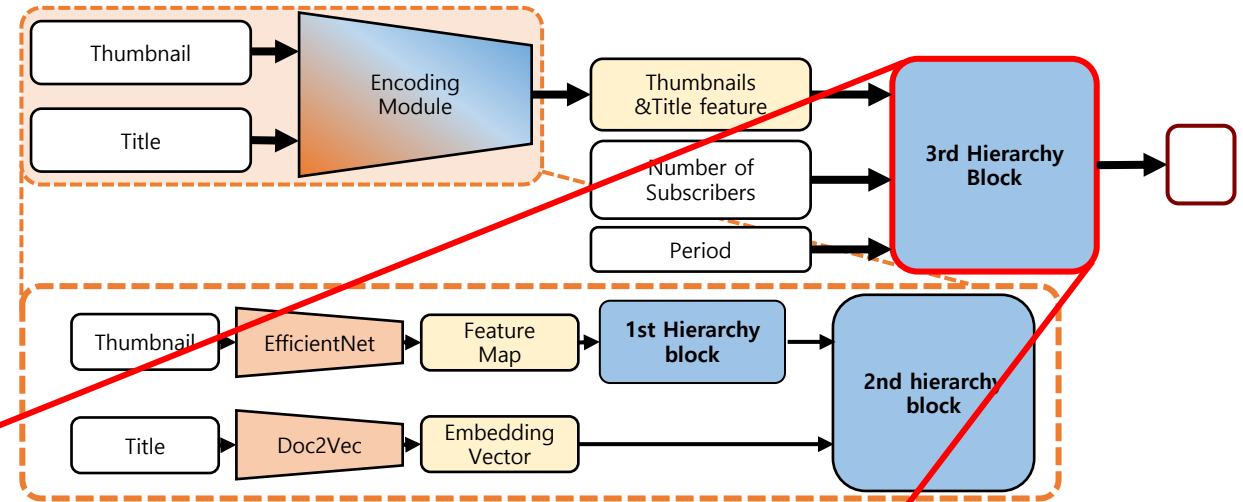
The output vector is a squeezed image and title feature vector with shape(10,1)



### 3<sup>rd</sup> Hierarchy Block

The final stage of our model

The output value is prediction of logarithm of view counts



## The effect of hierarchical model

The model can learn with balanced size of inputs

Input type	Shape of vector
Thumbnail	(320,6,10)
Title	(10,1)
Upload period	(1,1)
Number of subscribers	(1,1)

After  
hierarchy blocks

Input type	Shape of vector
Thumbnail and Title	(10,1)
Upload period	(1,1)
Number of subscribers	(1,1)

More balanced input  
size than before!

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## Experiment Setting



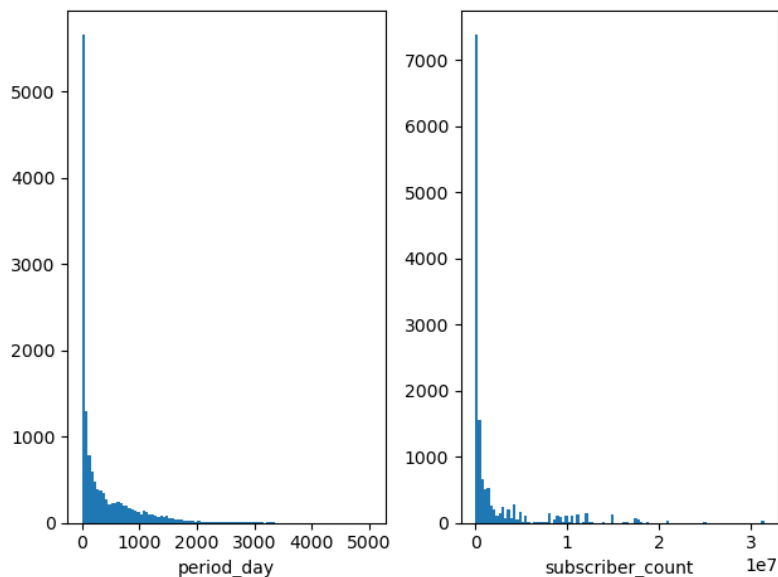
## Data z-score Normalization

For **Period** and **Number of Subscribers** data

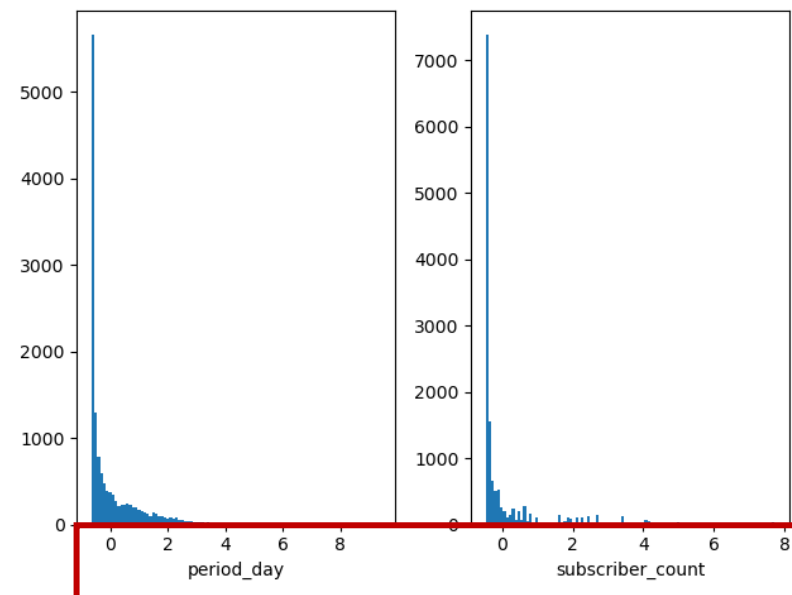
When learning with small data set without preprocessing, MSE loss popped up in the middle of learning.

We estimated that the cause was that the **range difference** between the two features was very **large**.

**Period\_day** range: 0 ~ 5020 / **Subscriber\_count** range: 0 ~ 3.14e+07



Scaling





## Baseline Models

- Simple linear regression model

- MLP model

  - Hidden layers: 20492 / 307 / 40 / 1

## Experiment Orders

- Optimize model architecture

- Explore optimal hyperparameters

- Train

- Evaluate results compared with baseline linear regression and MLP models

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## Evaluation

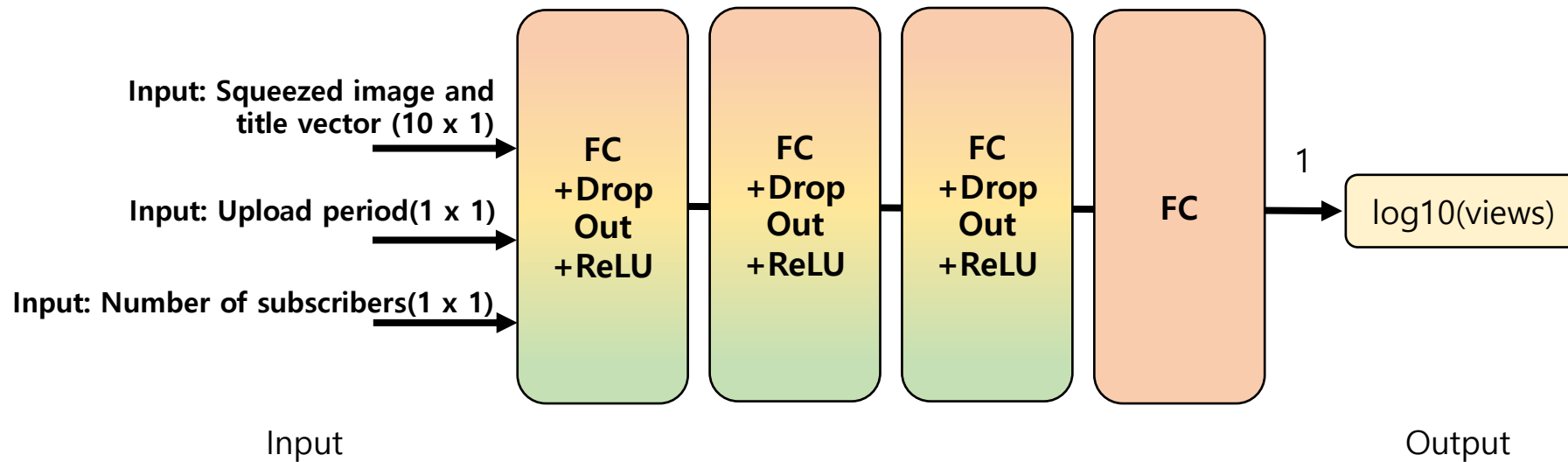
## Model Design Configuration

Use small part of dataset: 1600 / 200 / 200 (8 : 1 : 1)

Add DropOut and more Hidden Layers

DropOut rate: 0.3

MSE (Test): 17.21



## Hyperparameter Derivation

K Fold Cross Validation,  $K = 3$

- epochs = 20
- optimizer = Adam
- learning rate = 0.001 / **0.0005** / .0001
- weight decay = **0** /  $1e-3$  /  $1e-5$

✓ Best MSE(Validation): **4.81**



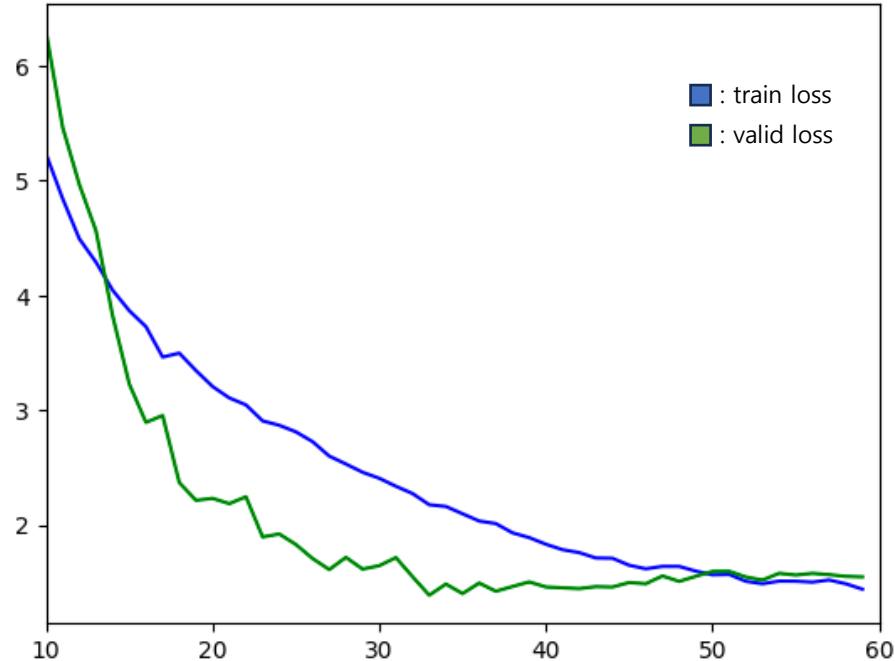
## Training Result

Hyper parameters: batch size = 64 / epochs = 60 / learning rate = 0.0005 / weight decay = 0

Early stopping at epoch 50

Small Dataset MSE ( $\text{Test}_{\text{Small}}$ ) : 17.21

Full Dataset MSE (Test) : **1.32** (▼15.89)



## Performance Comparison

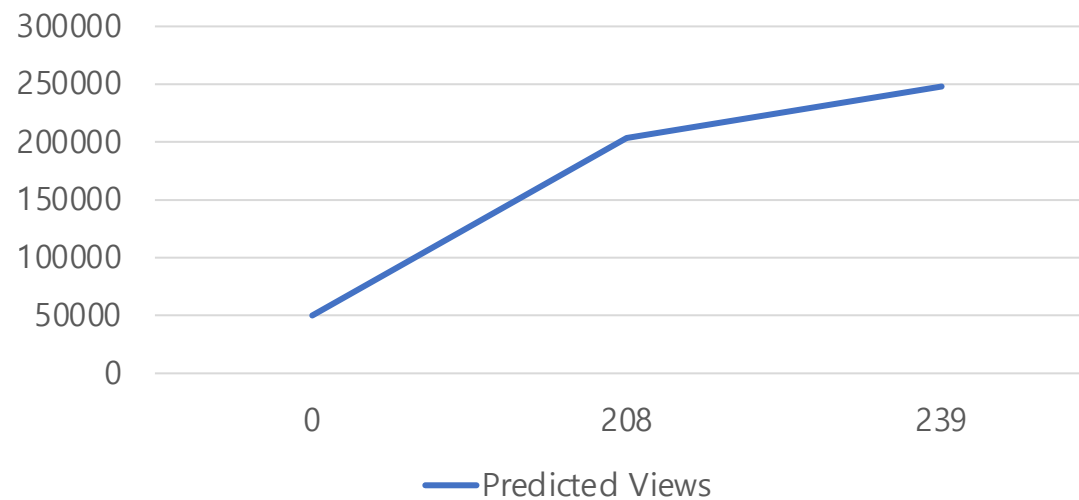
	Baseline Linear Regression	Baseline MLP	Ours
MSE	2.34	1.63	<b>1.32</b>
$\Delta$ MSE	▲1.02	▲0.31	-
# Parameters	-	6,303,712 (▲8,301)	<b>6,295,411</b>

## Sample Output



Current View Count: 360K

Predicted Views



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## Conclusion

## Analysis

Our novelty

The result of the feature importance shows that **utilizing thumbnail feature is important for predicting view counts**

People click upon inherent features of thumbnails

**Our model is performs better** than baseline MLP model with fewer parameters with MSE of **1.32** (▼1.02 in **logarithm**)

Sophisticated architecture to balance between features