Predicting Popularity in Korean Drama Industry Based on Face Image

Jackson Tin,

General Assembly

Problem

- South Korean entertainment industry is fiercely competitive and burgeoning with potential talents
- Current manual scouting methods may not fully capture the breadth of this potential
- Subject to the bias of the individual talent scouts themselves

Motivation

Develop a predictive model that uses face images to assess potential success in the Korean entertainment industry

Automate screening of candidates by feeding the face images to the model to predict potential success based on data

For myself, a fun project to take on

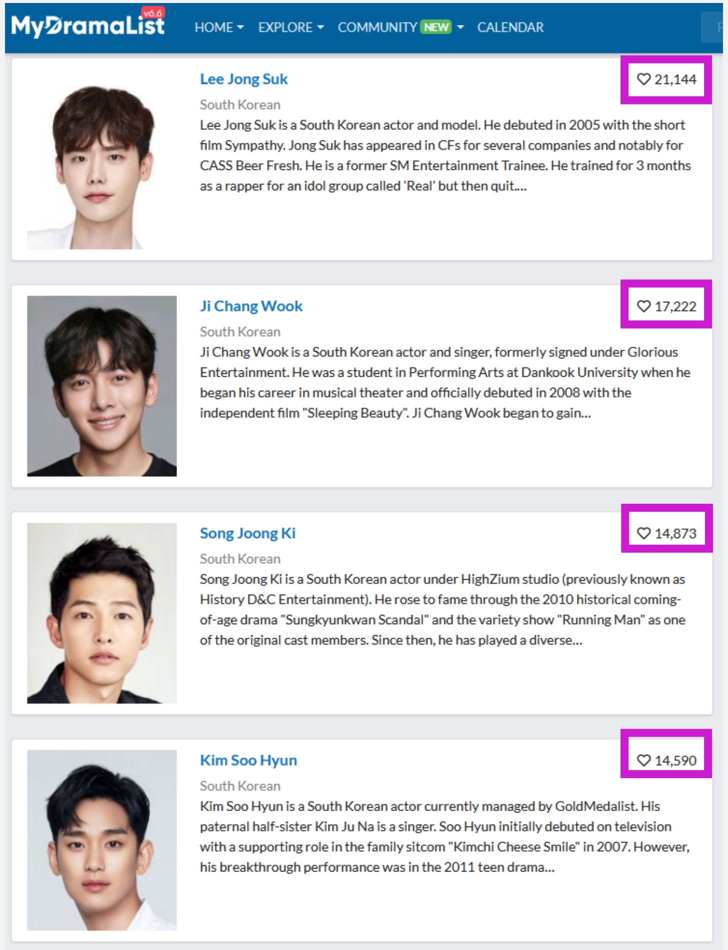
What is Success?

For the purposes of developing a prototype:

Popularity level of **male South Korean** actors based on mydramalist.com will be used to gauge success

For future works, other metrics such as net worth, brand endorsements etc. can be factored in when resources are available

Popularity on mydramalist.com



+ Users give a “heart” to actors they like.
+ For each actor, users can only give a “heart” once
+ Users can give a “heart” to more than one actor
+ The higher the “hearts”, the more popular the actor

General Workflow

Scrape	Scrape names, number of “hearts”, and face images of male South Korean actors in descending popularity order
Assign tier	Put names and number of “hearts” in a dataframe, assign popularity tier to the actors based on popularity
Sort	Sort face images into 2 image folders, “very popular” and “not so popular” based on popularity tier
Build/refine models	Build and refine machine learning models
Finalise model	Finalise model and deploy prototype

Scraping and Data Collection

1. Use BeautifulSoup to scrape names, number of “hearts” and hyperlinks of the face images for South Korean Male actors

2. Remove duplicate names, keep first entry

3. Modify the last letter of each hyperlink to access the higher resolution version of the face images

4. Download all face images with requests.get()

5. Assign actors in dataframe to “very popular” tier or “not so popular” tier based on number of “hearts”

Scraping and Data Collection

241

actors in very popular tier

249

actors in not so popular tier

Very Popular Tier


Lee Jong Suk


Ji Chang Wook


Park Seo Hoon


Song Joong Ki

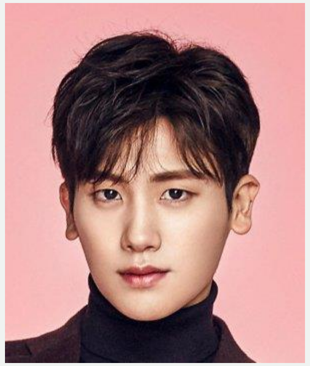

Kim Soo Hyun


Lee Min Ho


Nam Joo Hyuk

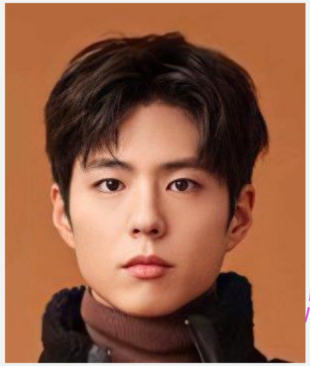

Lee Joon Gi


Lee Dong Wook

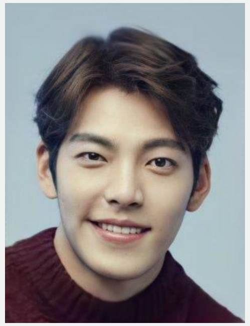

Park Hyung Sik


Ji Sung


Gong Yoo


Park Bo Gum

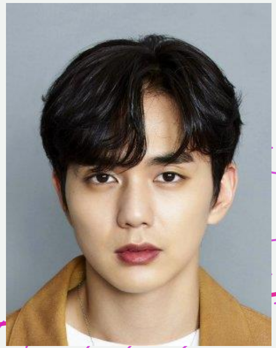

Seo In Guk


Kim Woo Bin


Lee Seung Gi


Cha Eun Woo

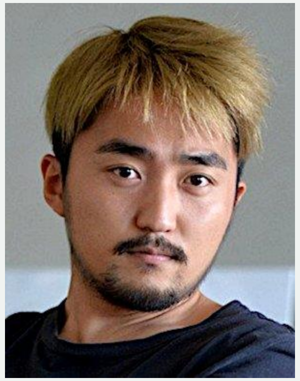

Hyun Bin


Yoo Seung Ho


Seo Kang Joon

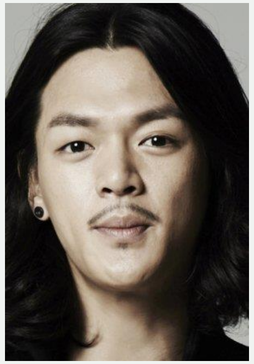
Not So Popular Tier


Kang Han Saem


Yoo Byung Jae


Jang Won Young


Park Sang Won

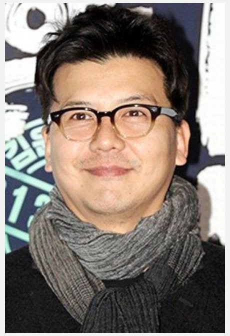

Choi Dong Goo

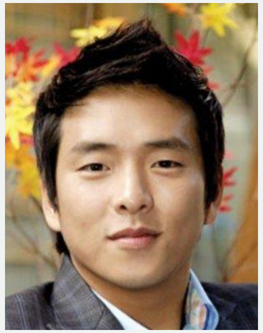

Ahn Sung Ki


B-Bomb


Kim Chung Soon


Tony Ahn


Son Ji Chang


Kim Dong Yoon


Kim Min Kyo

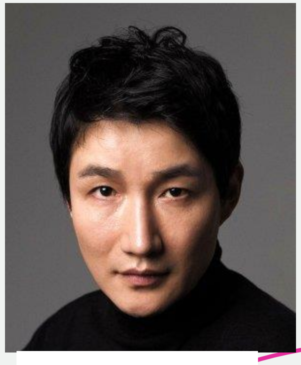

Kim Tae Hyung


Kwon Hyuk Soo


Lee Seung Hyo


Lee Young Hoon


Park Geun Hyung


Heo Dong Won

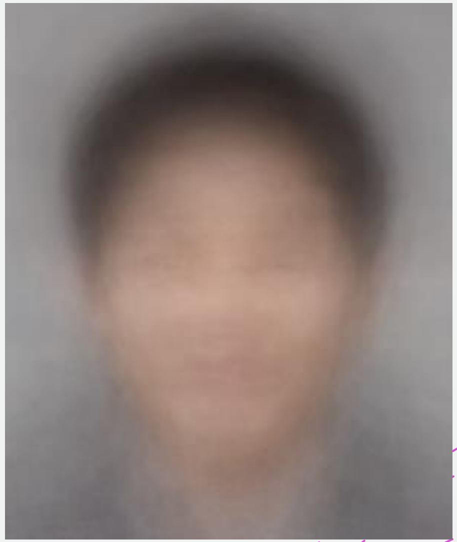

Park Yong Woo


Shin Seung Hwan

Average face of top 20 very popular actors

Average face of all 241 very popular actors

Average face of 20 not so popular actors

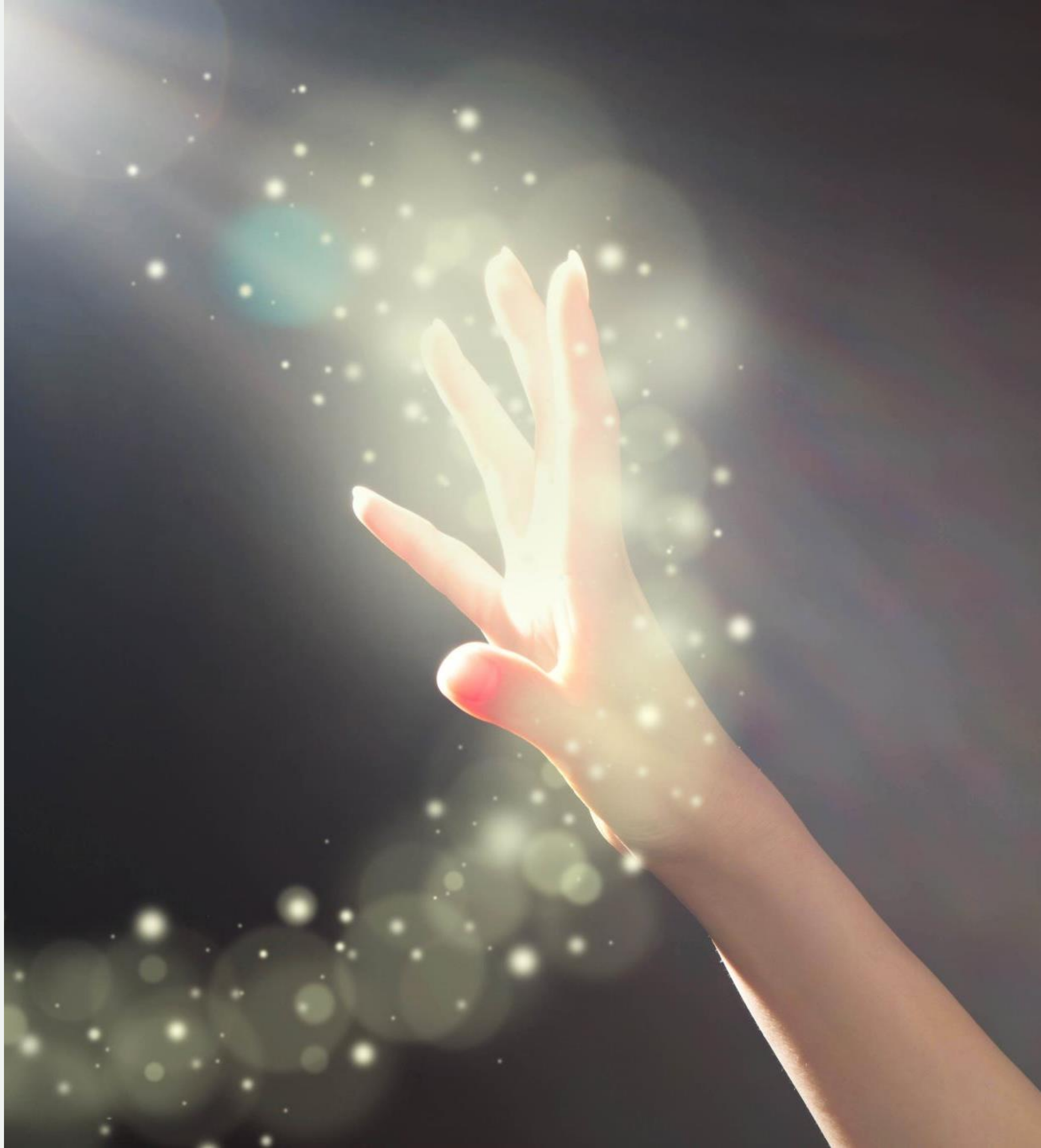


Average face of all 249 not so popular actors

Why do looks matter?

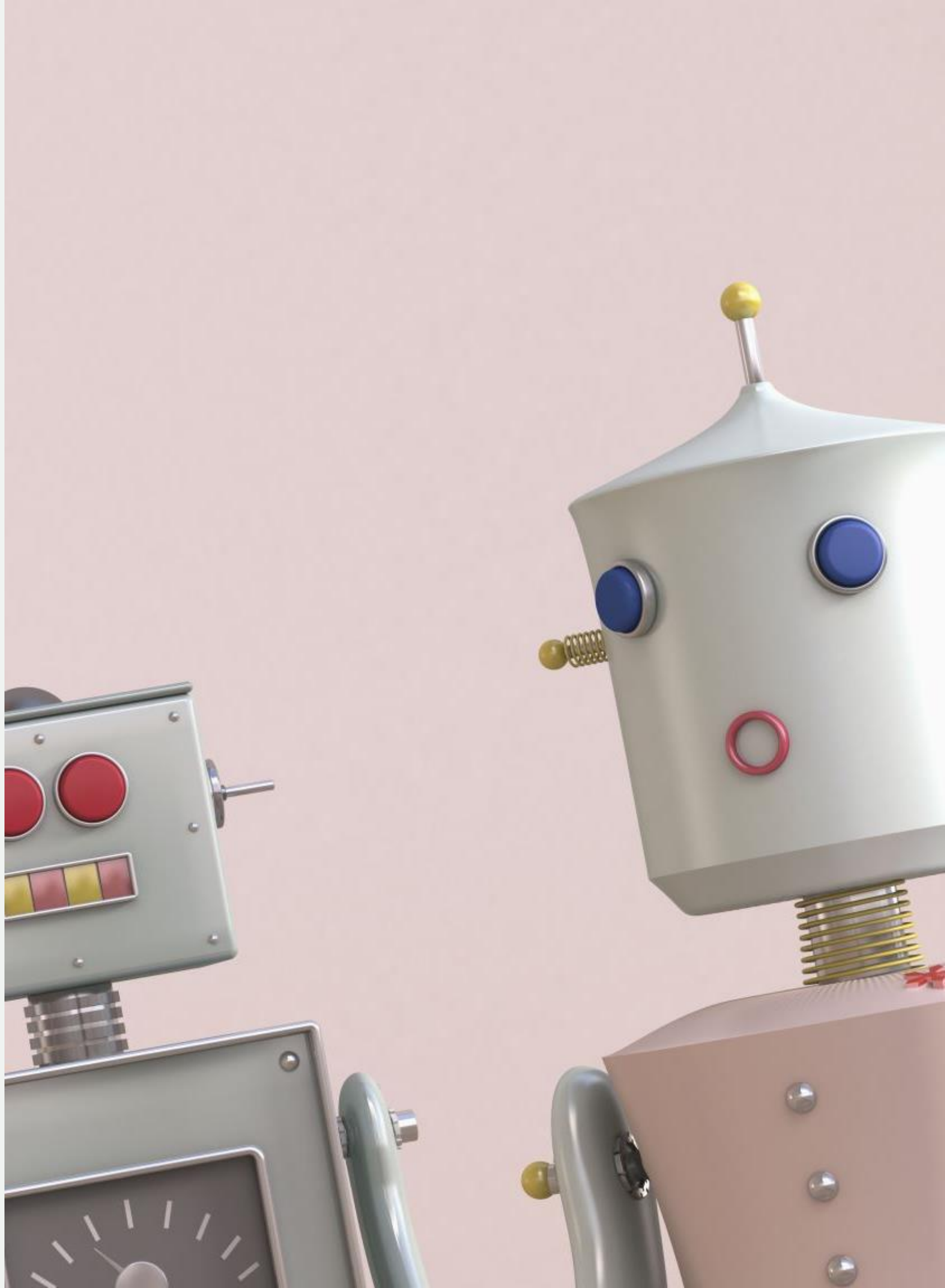
Looks are not everything, but..

+ Your visuals make the first impression, more so in the entertainment industry
+ Looks also contribute to the halo effect, where good-looking people are perceived as a good or talented person
+ For other things like acting skills, dancing skills, vocals, these can be trained



What constitutes facial attractiveness?

- **Facial averageness**
  - With some parameters, it's beneficial to be above average or away from the norm to achieve that 'model tier' look, while for others a sizable deviation can exponentially hurt the subject's aesthetic harmony
- **Symmetry**
- **Youthfulness**
- **Sexual dimorphism**
  - Facial sexual dimorphism emerges at puberty: as the size and shape of the male and female faces increase with age, faces begin to show different secondary sexual characteristics (i.e., masculine or feminine)
  - For example, male jawbones become larger, cheekbones more prominent, cheeks and lips thinner



Youthfulness

+ Significant emphasis on maintaining a youthful, almost boyish look

Sexual dimorphism

+South Korean male beauty standards are unique

Masculine Features

- Sharp, V-shaped or a slightly rounded jawline
- High, defined cheekbones

Non-Traditional/Masculine Features

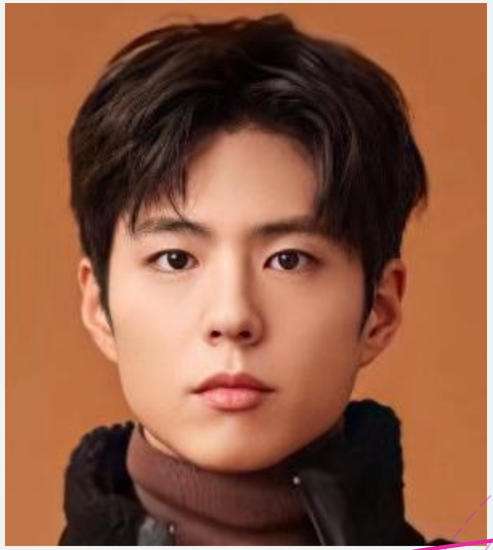
- Pale and flawless skin
- Plump lips
- Slim face
- Cosmetics

Other Societal/Trendy Features

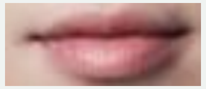
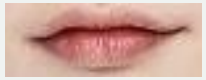
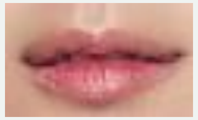
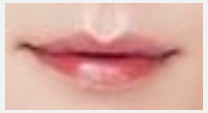
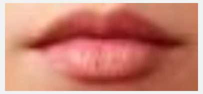
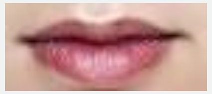
- Double eyelids, big eyes
- Well-defined nose, high nose bridge
- Clean look
- Hairstyle



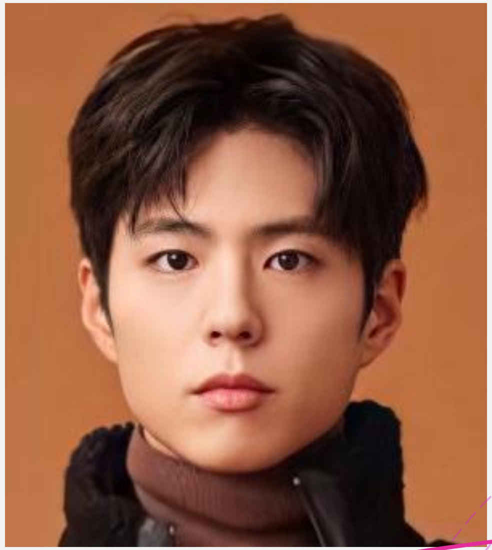
- Sharp jawline
- High, defined cheekbones

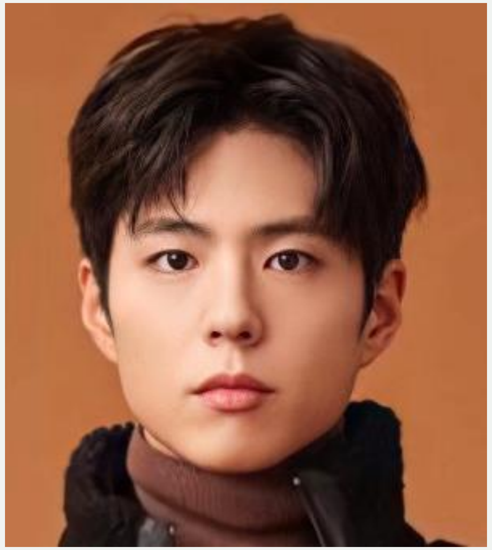

- Plump lips
- Cosmetics

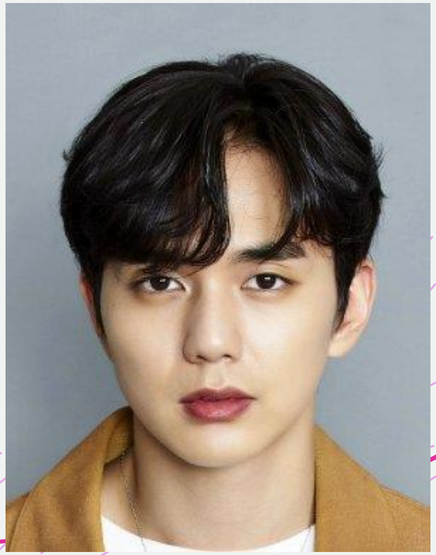









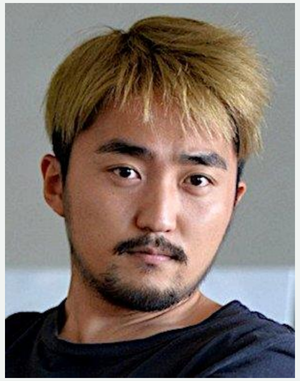

- Hairstyle
- Clean-shaved look





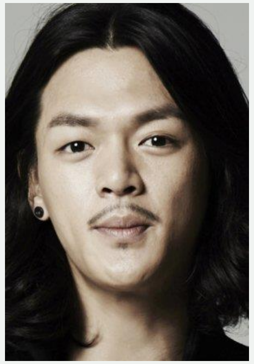
Not So Popular Tier


Kang Han Saem


Yoo Byung Jae


Jang Won Young


Park Sang Won

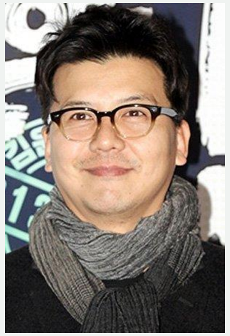

Choi Dong Goo

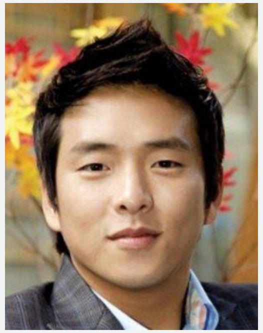

Ahn Sung Ki


B-Bomb


Kim Chung Soon


Tony Ahn


Son Ji Chang


Kim Dong Yoon


Kim Min Kyo

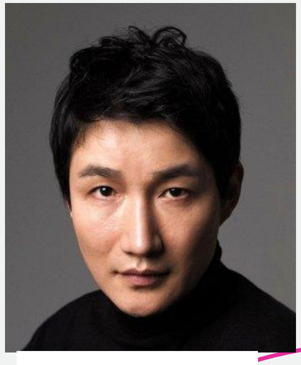

Kim Tae Hyung


Kwon Hyuk Soo


Lee Seung Hyo


Lee Young Hoon


Park Geun Hyung


Heo Dong Won


Park Yong Woo


Shin Seung Hwan

Feature Extraction – VGG16

- VGG16 is a type of pretrained convolutional neural network (CNN) model that is commonly used for object detection and classification

- VGG16 takes an image as input and passes it through its network layers. Each layer learns to recognize different features in the image.
    - Early layers detect simple features like edges and curves,
    - Deeper layers recognize more complex features like shapes, patterns, or objects.

- Take out the top layer, i.e. the classification layer, to output numerical representation of the image that encapsulates the features the model has learned

col_9	...	col_25079	col_25080	col_25081	col_25082	col_25083	col_25084	col_25085	col_25086	col_25087	col_25088
0.0	...	0.0	0.0	0.0	0.0	3.9212093	0.0	0.0	0.027669907	0.0	very_popular
0.0	...	0.0	0.0	5.1023827	1.3957657	0.0	0.0	0.0	17.52898	0.0	very_popular
0.0	...	0.0	0.0	0.0	98.71404	0.0	0.0	0.0	0.0	0.0	very_popular
0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.752463	0.0	very_popular
0.0	...	0.0	6.256437	3.4620895	0.0	0.0	0.0	0.0	0.0	0.0	very_popular
...	...	...	...	...	...	...	...	...	...	...	...
0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	20.953001	0.0	not_so_popular
0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	not_so_popular
0.0	...	0.0	0.0	0.0	0.0	16.664928	0.0	0.0	7.663937	0.0	not_so_popular
0.0	...	7.1930723	0.0	9.211779	0.0	0.0	15.40993	0.0	0.0	0.0	not_so_popular
0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	19.3946	0.0	not_so_popular

- Each column is a feature

Building the Models

1. Logistic Regression (lr)
2. K Neighbours Classifier (knn)
3. Ada Boost Classifier (ada)
4. Extreme Gradient Boosting (xgboost)
5. Gradient Boosting Classifier (gbc)
6. Light Gradient Boosting Machine (lightgbm)
7. Random Forest Classifier (rf)
8. SVM
9. Decision Tree Classifier (dt)
10. Extra Trees Classifier (et)
11. Linear Discriminant Analysis (lda)
12. Quadratic Discriminant Analysis (qda)
13. Ridge Classifier (ridge)

VGG16 Base Feature Extraction Model

	Best Model		Accuracy	AUC	Recall	Precision	f1-score
Train Size 0.7, 10 folds	xgboost	Train	0.8649	0.9262	0.8501	0.8726	0.8611
		Test	0.7957	0.8637	0.7868	0.8023	0.7917
Train Size 0.7, 5 folds	xgboost	Train	0.8571	0.9266	0.8432	0.8636	0.8532
		Test	0.7960	0.8622	0.7870	0.7975	0.7920
Train Size 0.65, 10 folds	xgboost	Train	0.8354	0.9017	0.8269	0.8363	0.8314
		Test	0.7674	0.8441	0.7687	0.7631	0.7631
Train Size 0.65, 5 folds	lightgbm	Train	0.8593	0.9205	0.8397	0.8689	0.8539
		Test	0.7925	0.8540	0.7562	0.8097	0.7811

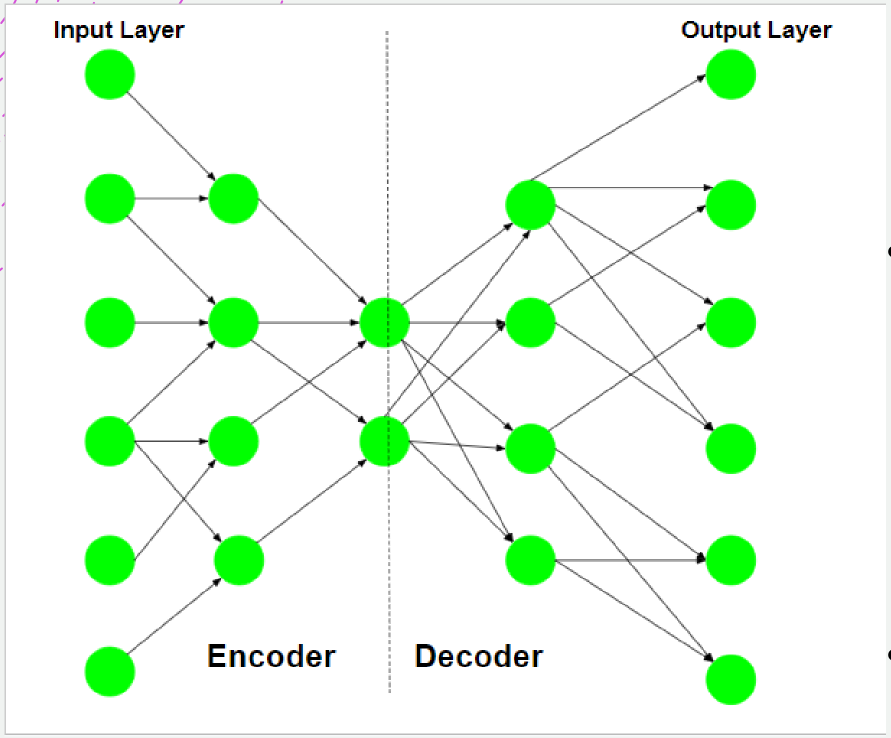
Problems:

- Models take hours to train
- When model is deployed, each prediction takes a long time

VGGFace Base Feature Extraction Model

	Best Model		Accuracy	AUC	Recall	Precision	f1-score
Train Size 0.7, 10 folds	et	Train	1.0000	1.0000	1.0000	1.0000	1.0000
		Test	0.7845	0.8699	0.7518	0.8172	0.7775
Train Size 0.7, 5 folds	xgboost	Train	0.8535	0.9441	0.8151	0.8787	0.8455
		Test	0.7347	0.8422	0.7046	0.7466	0.7232
Train Size 0.6, 10 folds	lr	Train	1.0000	1.0000	1.0000	1.0000	1.0000
		Test	0.7721	0.8498	0.7457	0.7926	0.7533
Train Size 0.6, 5 folds	xgboost	Train	0.8563	0.9416	0.8138	0.8860	0.8481
		Test	0.7724	0.8433	0.7241	0.7947	0.7567

Feature Extraction – VGG16 + Autoencoder



- An autoencoder is a type of artificial neural network used for learning efficient codings of input data, i.e.:
  - Reduces dimensionality of the data
  - Retain only the most important features of the data

- Consists of two main parts:
  - **Encoder**: Encodes the input image as a compressed representation in a reduced dimension. The compressed image typically contains the main attributes of the original image.
  - **Decoder**: Aims to reconstruct the input and decodes the compressed image back into the original image

- Goal is to make our image classification model **simpler** (as it takes input of lower dimension) and faster (as there's less data to process) without sacrificing too much performance

Feature Extraction – VGG16 + Autoencoder

	Best Model		Accuracy	AUC	Recall	Precision	f1-score
Batch Size 256, 5 folds, 50 epochs	gbc	Train	1.0000	1.0000	1.0000	1.0000	1.0000
		Test	0.7725	0.8369	0.7756	0.7696	0.7708
Batch Size 512, 5 folds, 50 epochs	lightgbm	Train	0.9971	1.0000	1.0000	0.9941	0.9971
		Test	0.7697	0.8512	0.7873	0.7611	0.7717
Batch Size 512, 5 folds, 50 epochs	xgboost	Train	0.7752	0.8806	0.7640	0.7765	0.7700
		Test	0.7520	0.8451	0.7456	0.7611	0.7498

Feature Extraction – VGGFace + Autoencoder

	Best Model		Accuracy	AUC	Recall	Precision	f1-score
Batch Size 32, 10 folds, 100 epochs	xgboost	Train	0.8478	0.9318	0.789	0.8901	0.8361
		Test	0.7550	0.8342	0.6923	0.7914	0.7333
Batch Size 32, 10 folds, 50 epochs	lightgbm	Train	0.8322	0.9165	0.8225	0.8347	0.8284
		Test	0.7642	0.8279	0.7643	0.7598	0.7586

Feature Extraction – EfficientNetB0 + Autoencoder

	Best Model		Accuracy	AUC	Recall	Precision	f1-score
Batch Size 512, 10 folds, 50 epoch	lr	Train	0.8452	0.9288	0.8573	0.8333	0.8451
		Test	0.8165	0.8847	0.8346	0.8101	0.8170
Batch Size 512, 5 folds, 50 epochs	lda	Train	0.8513	0.9232	0.8521	0.8472	0.8496
		Test	0.8194	0.8853	0.8226	0.8137	0.8163
Batch Size 512, 10 folds, 25 epochs	et	Train	0.8141	0.8831	0.8481	0.7904	0.8181
		Test	0.8018	0.8605	0.8456	0.7775	0.8080
Batch Size 512, 5 folds, 25 epochs	et	Train	0.8455	0.9236	0.8772	0.8214	0.8483
		Test	0.8046	0.8740	0.8342	0.7849	0.808
Batch Size 256, 10 folds, 25 epochs	et	Train	0.9129	0.9842	0.9329	0.8947	0.9134
		Test	0.8191	0.8790	0.8338	0.8174	0.8206
Batch Size 128, 10 folds, 100 epochs	ada	Train	0.8795	0.9610	0.8843	0.8729	0.8785
		Test	0.8022	0.8871	0.7926	0.8101	0.7976
Batch Size 32, 10 folds, 50 epochs	lda	Train	0.8264	0.9072	0.8448	0.8108	0.8274
		Test	0.8134	0.8872	0.8283	0.8091	0.8149

Feature Extraction – VGG16 + Autoencoder

	Best Model		Accuracy	AUC	Recall	Precision	f1-score
Batch Size 256, 5 folds, 50 epochs	gbc	Train	1.0000	1.0000	1.0000	1.0000	1.0000
		Test	0.7725	0.8369	0.7756	0.7696	0.7708
Batch Size 512, 5 folds, 50 epochs	lightgbm	Train	0.9971	1.0000	1.0000	0.9941	0.9971
		Test	0.7697	0.8512	0.7873	0.7611	0.7717
Batch Size 512, 5 folds, 50 epochs	xgboost	Train	0.7752	0.8806	0.7640	0.7765	0.7700
		Test	0.7520	0.8451	0.7456	0.7611	0.7498

Best Model

Model Type		Best Model		Accuracy	AUC	Recall	Precision	f1-score
EfficientNetB0 + Autoencoder	Batch Size 512, 5 folds, 50 epochs	lda	Train	0.8513	0.9232	0.8521	0.8472	0.8496
			Test	0.8194	0.8853	0.8226	0.8137	0.8163
VGG16	Train Size 0.7, 5 folds	xgboost	Train	0.8571	0.9266	0.8432	0.8636	0.8532
			Test	0.7960	0.8622	0.7870	0.7975	0.7920
VGG16 + Autoencoder	Batch Size 512, 5 folds, 50 epochs	xgboost	Train	0.7752	0.8806	0.7640	0.7765	0.7700
			Test	0.7520	0.8451	0.7456	0.7611	0.7498
VGGFace	Train Size 0.6, 5 folds	xgboost	Train	0.8563	0.9416	0.8138	0.8860	0.8481
			Test	0.7724	0.8433	0.7241	0.7947	0.7567
MobileNet + Autoencoder	Batch Size 512, 10 folds, 50 epochs	rf	Train	0.8105	0.8875	0.8402	0.7891	0.8137
			Test	0.7725	0.8389	0.7868	0.7612	0.7735

Future Work

- Expand definition of success to include more metrics including **net worth**, **brand endorsements**, **drama ratings** and others
- Expand **regional scope** to Japan, Taiwan, outside of Asia
- Add **more actors**, as well as many **more images** per actor
- Train using **neural networks** when there are more data, and explore adding a third class of popularity
- Deploy model on a platform with **more capabilities** such as **batch upload** and **dashboard**