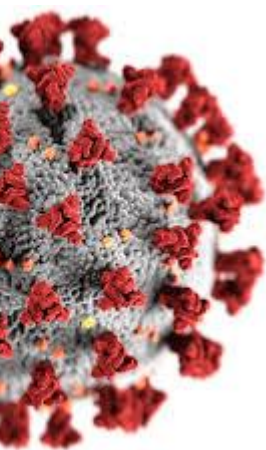




Tourists at Home

Exploring the contours of Domestic Tourism and to provide insights into how STB can market and position themselves to build an active and robust Domestic Tourism market.



\$\$ 365, 000, 000

As representatives of STB, we want to identify focus areas of high potential for the next phase of the **#SingapoRediscover**s campaign, and in turn propose targeted initiatives that can build up a resilient Domestic Tourism economy.

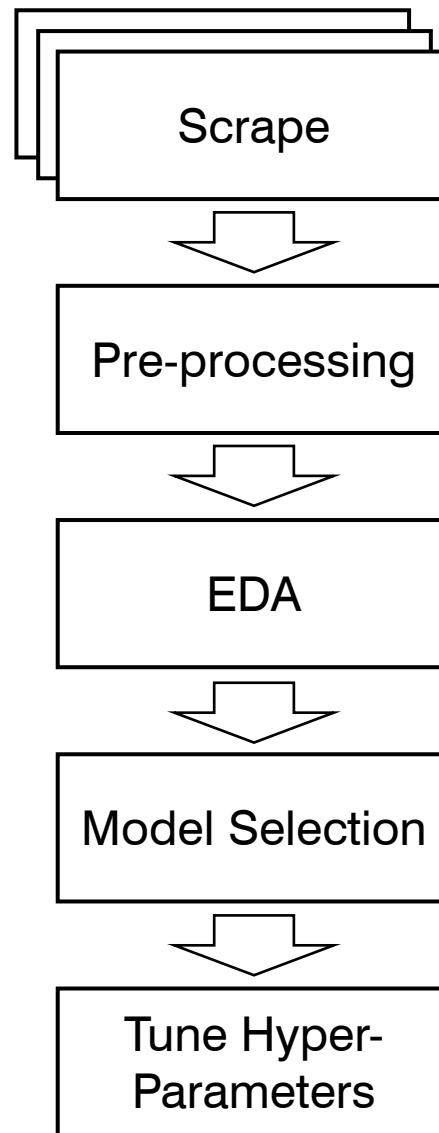
It is also this project's belief that investing in Domestic Tourism today can only add value to Singapore Tourism when travel finally resumes.

Problem Statement

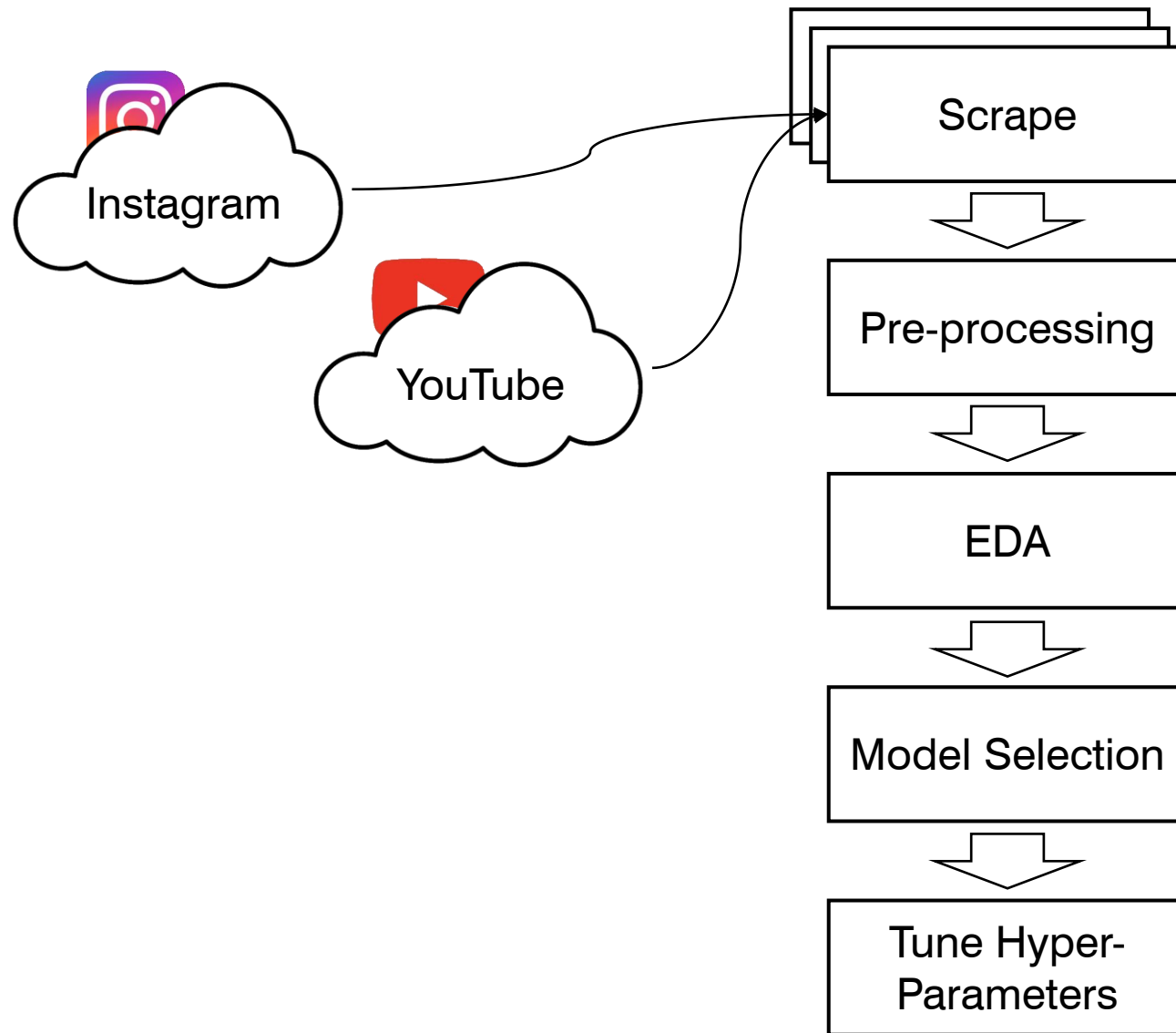
Process



Overview of Data Science process.

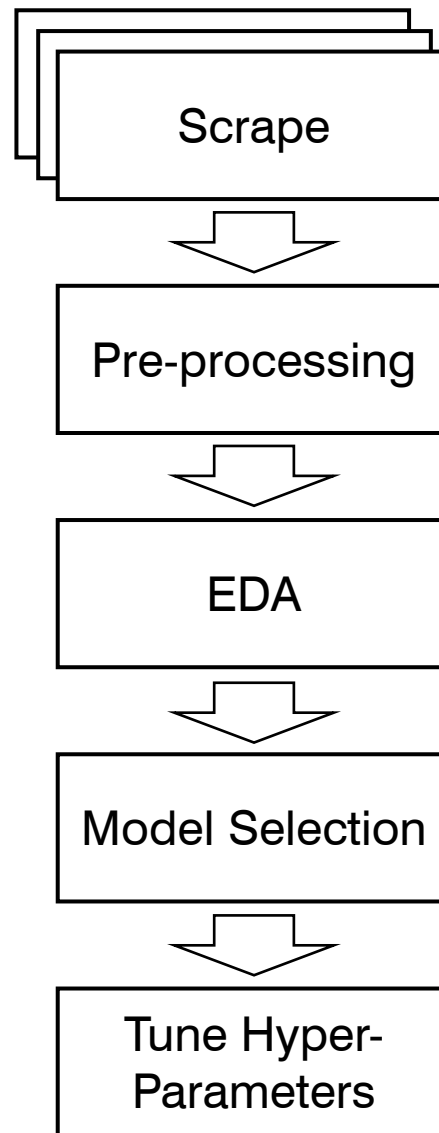


Methodology

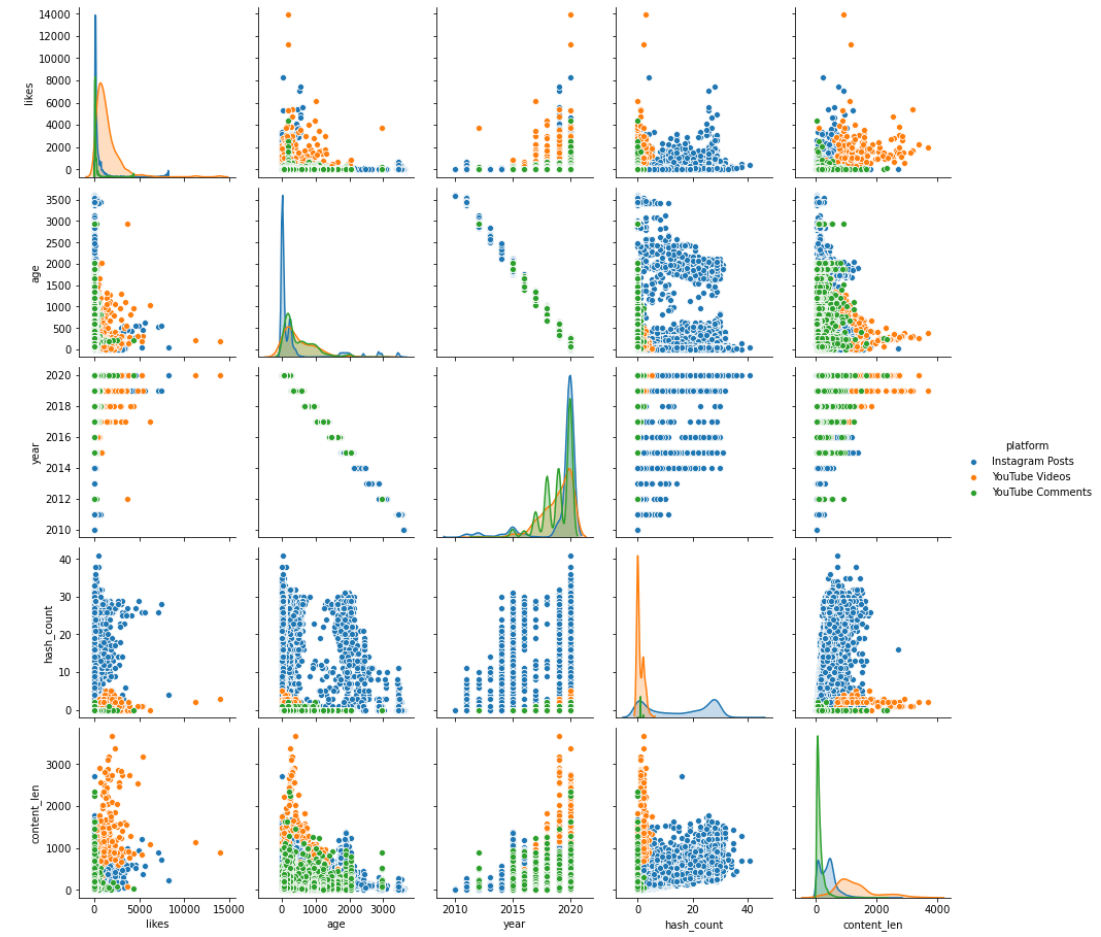
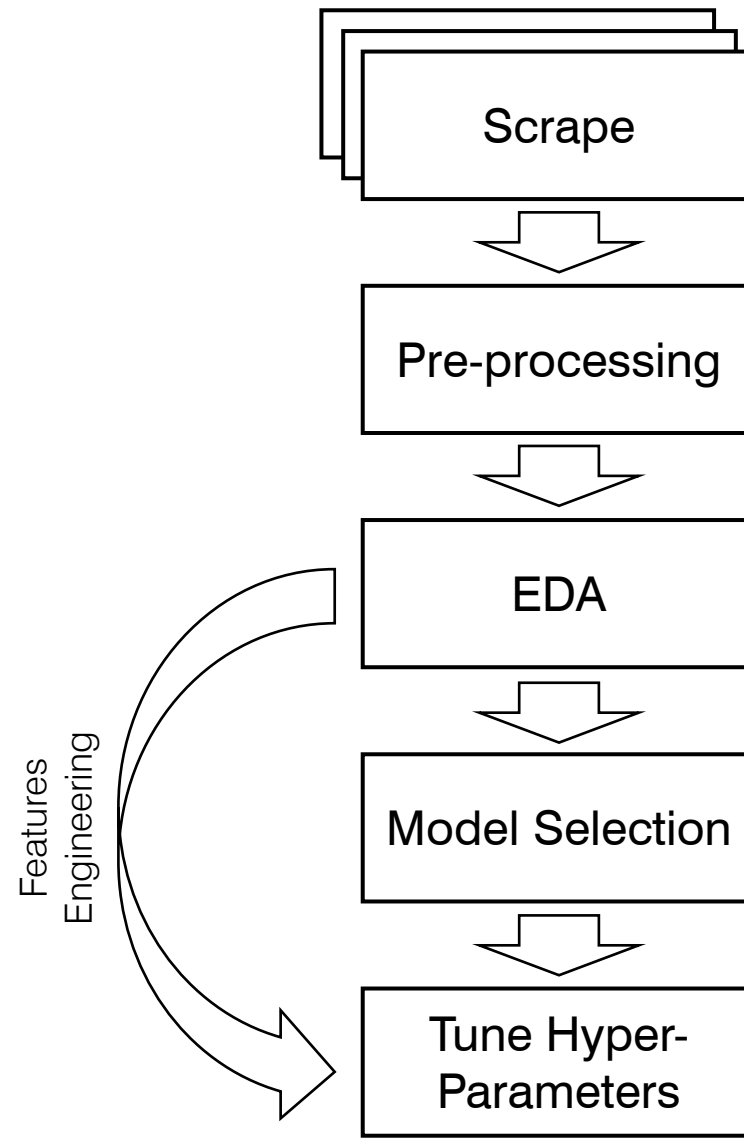


Methodology

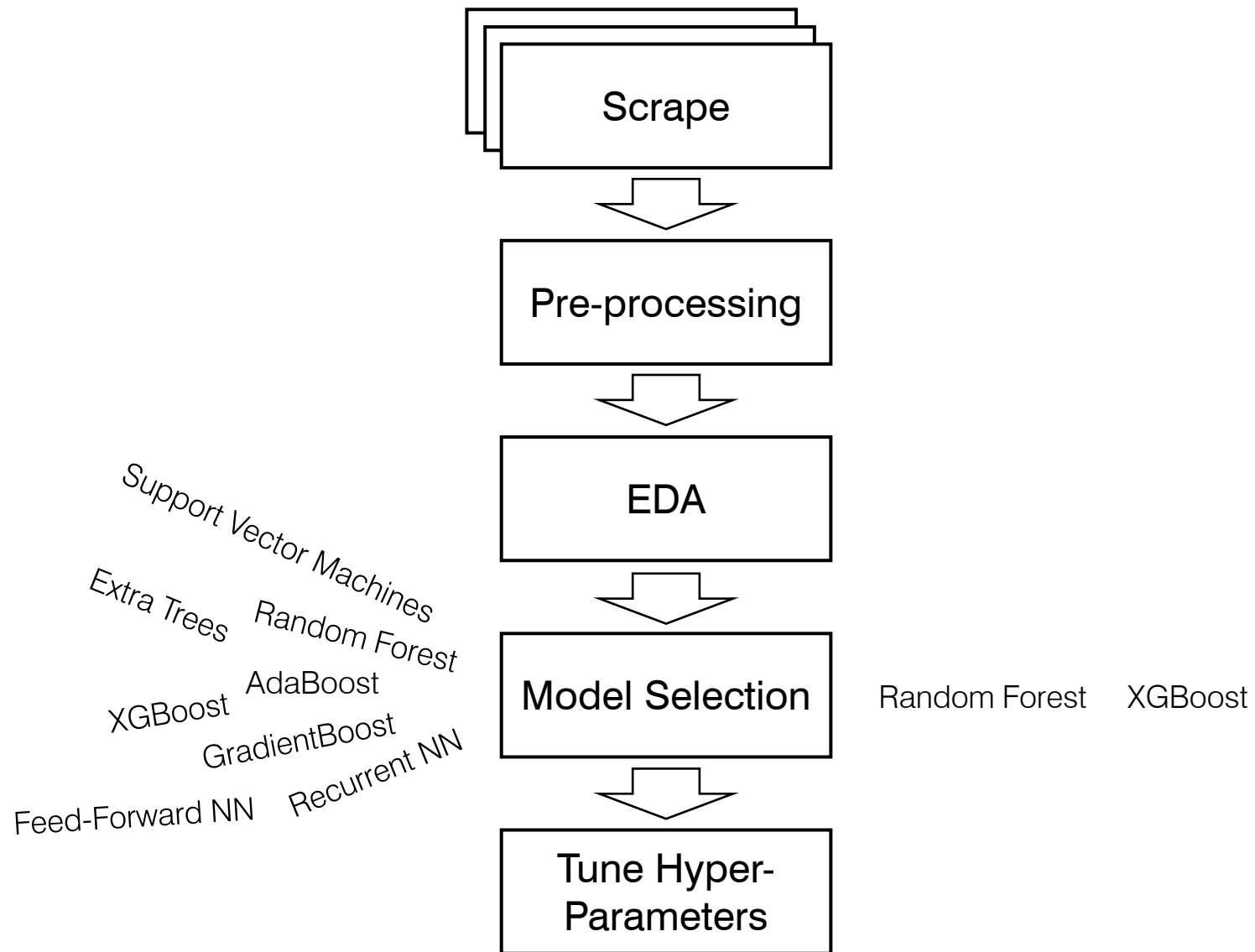
Data Cleaning
Ignore item non-response
Deductive imputation
Inferential imputation



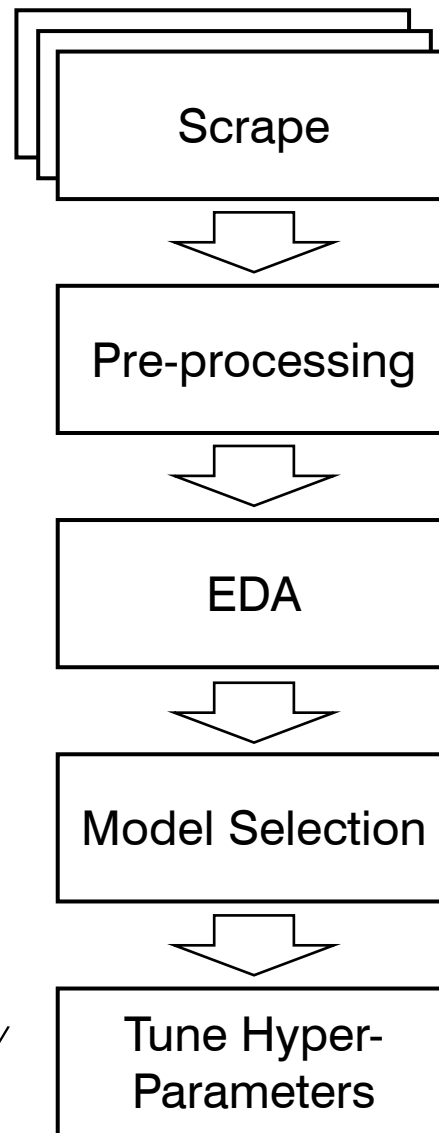
Methodology



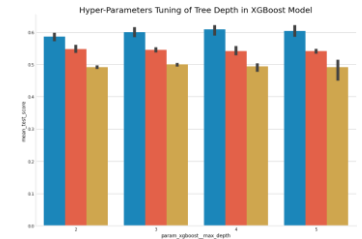
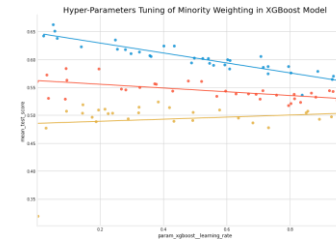
Methodology



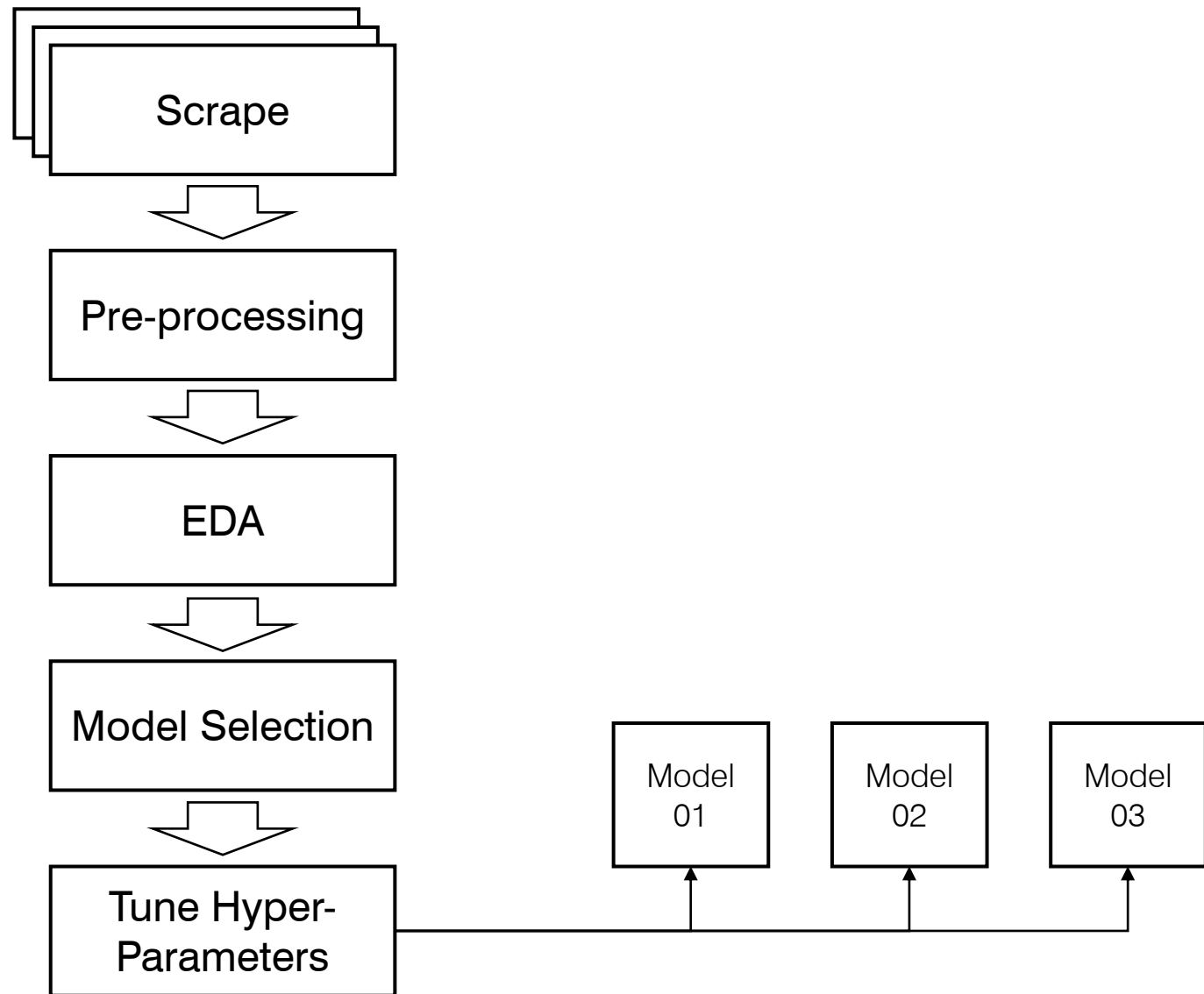
Methodology



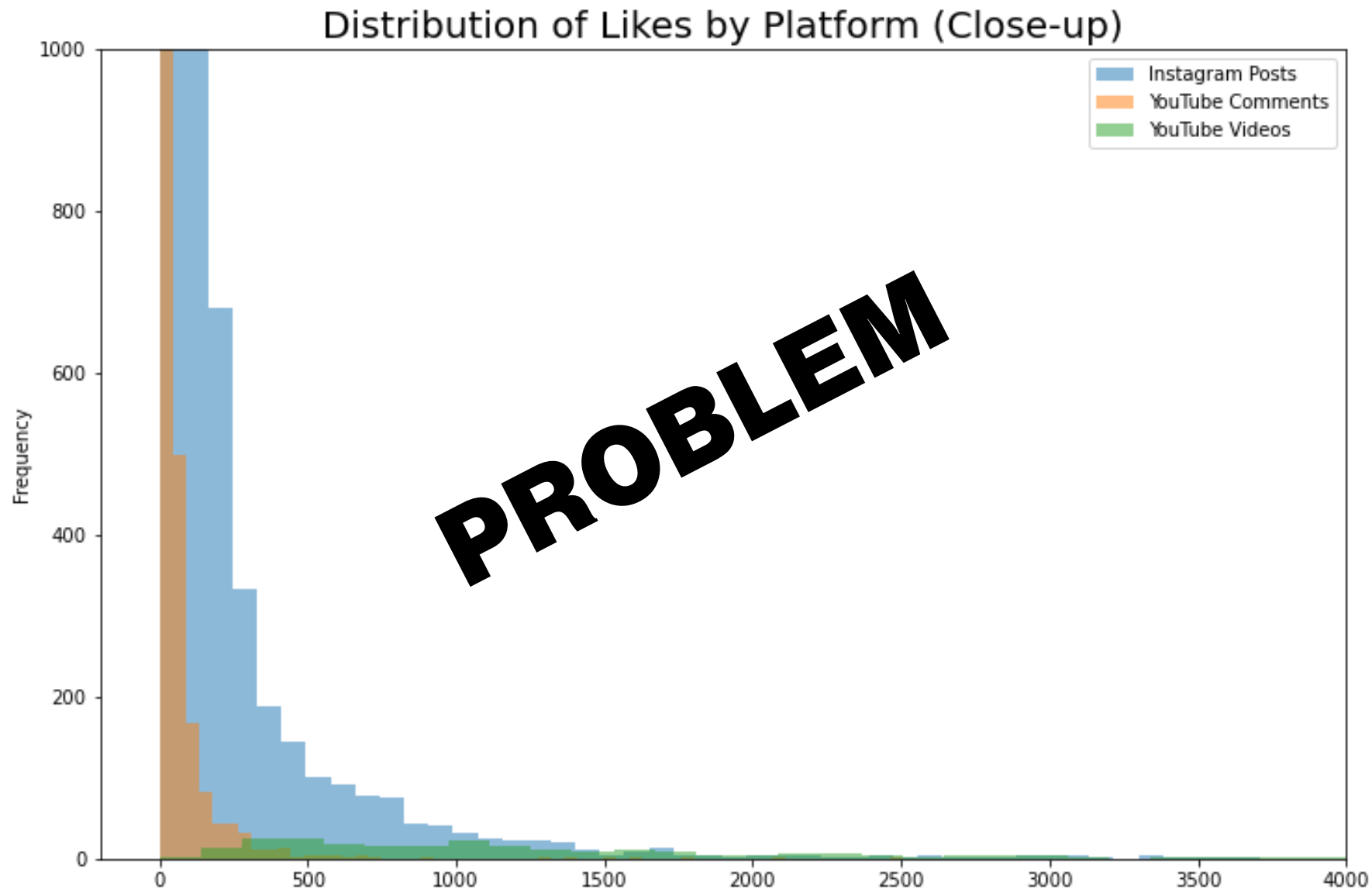
RandomizedSearchCV
GridSearchCV



Methodology



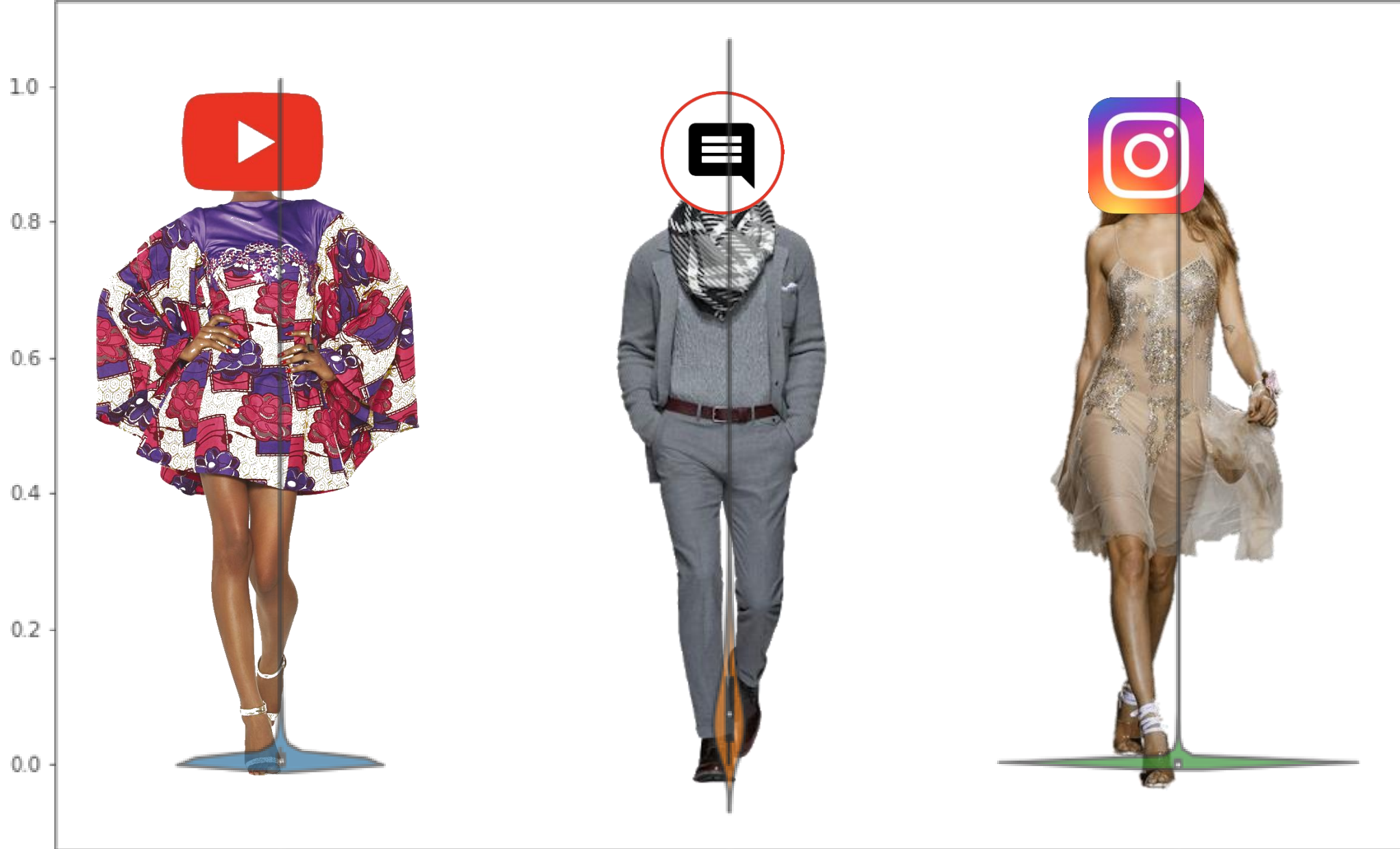
Methodology



I Like, You Like?



Platform Dummies



Rescale Target Variables



Separate Models

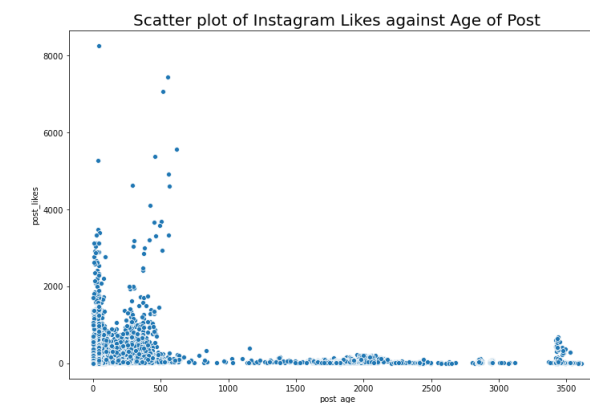
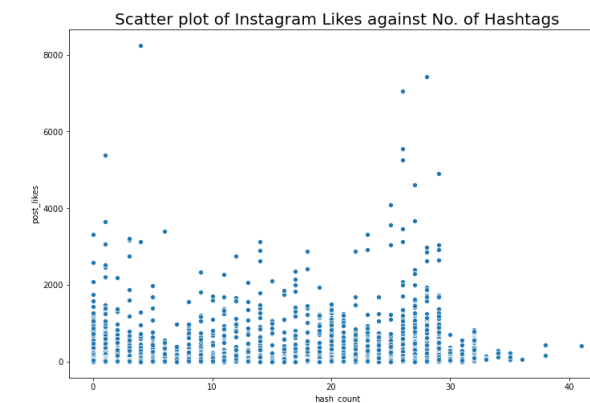
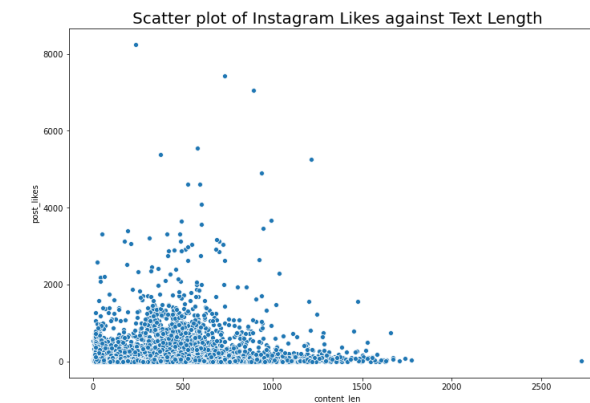
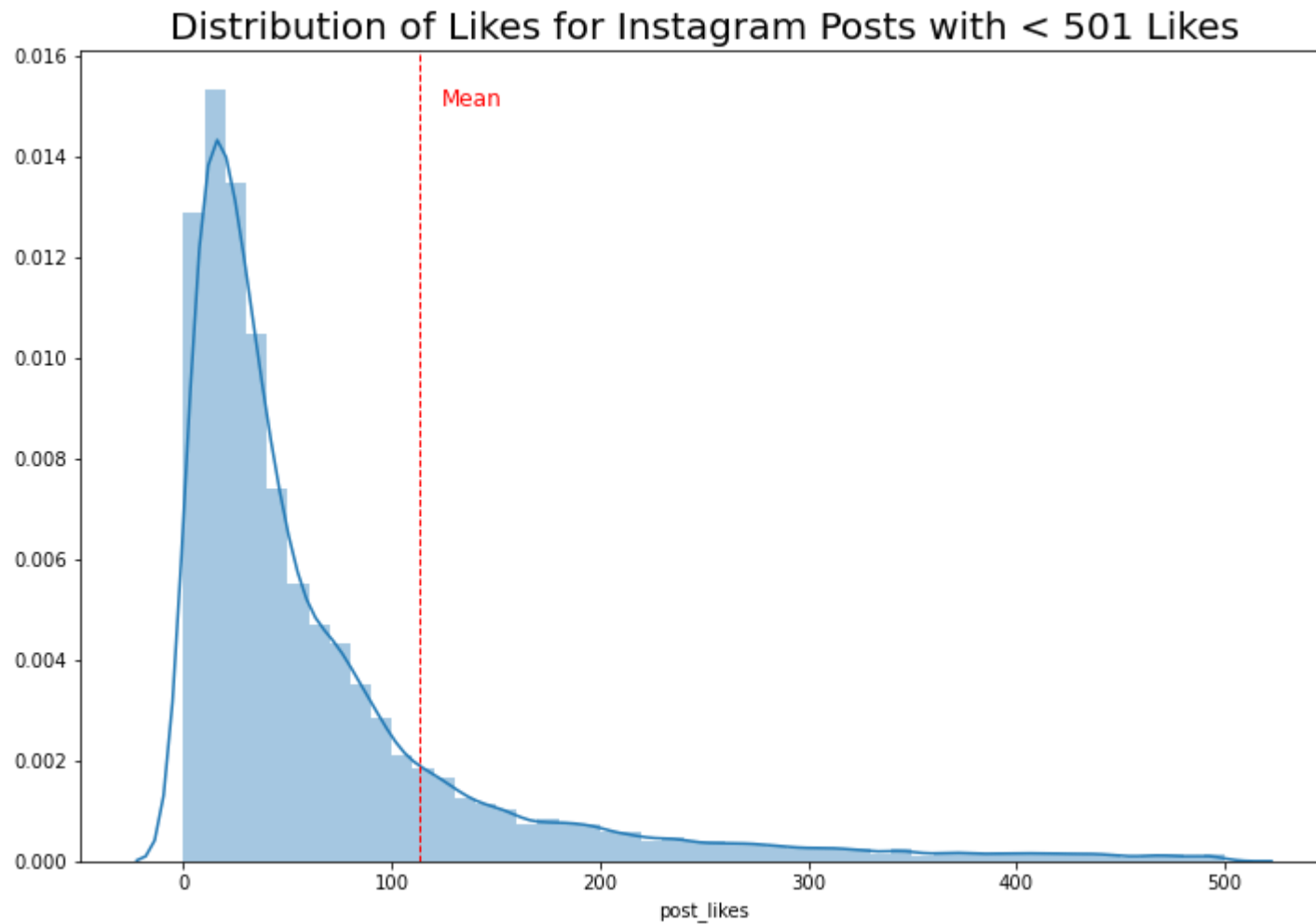


CLASSIFICATION

Create Target Labels

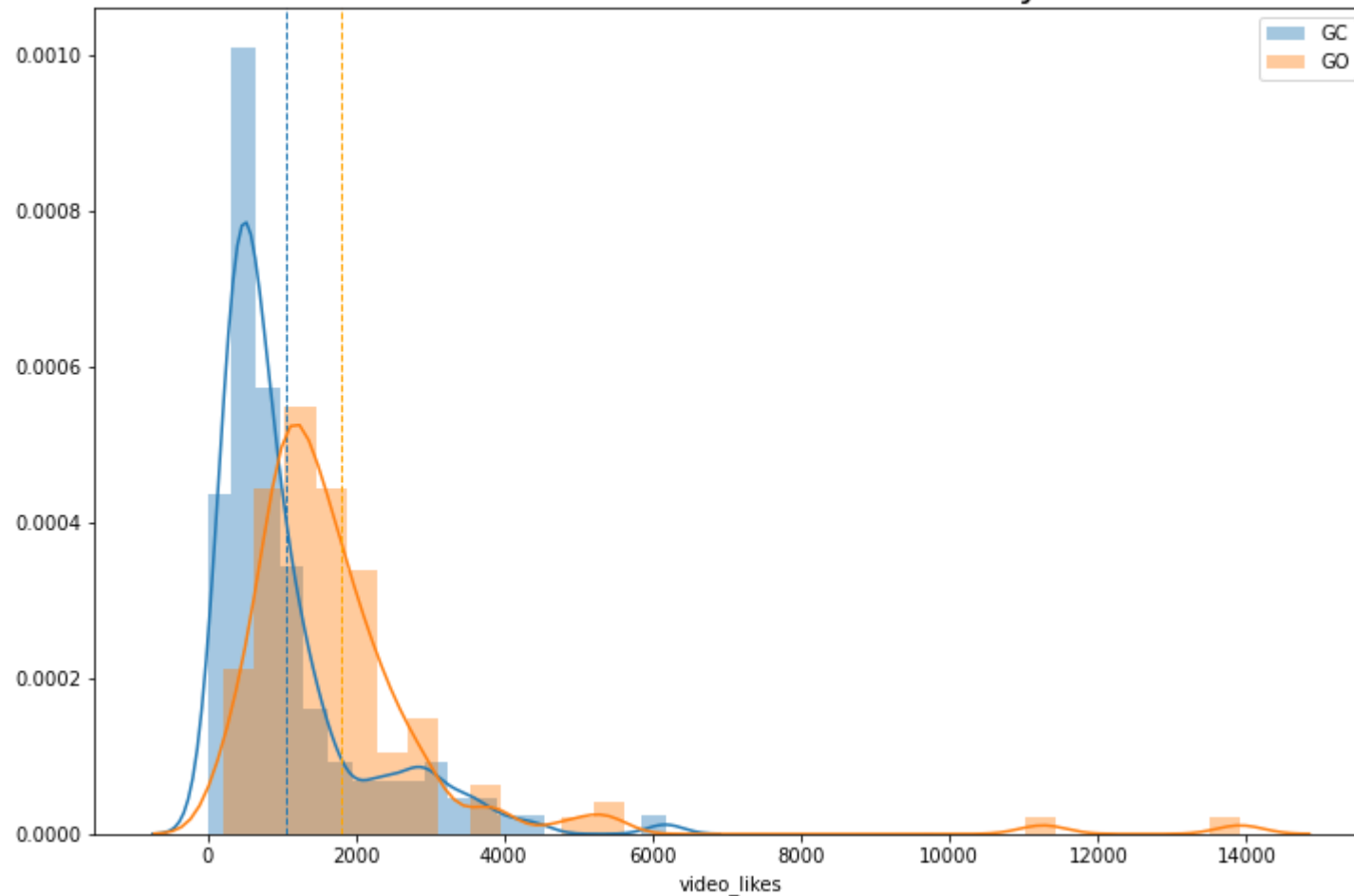
Exploratory Data Analysis

Preliminary analysis of data sets.

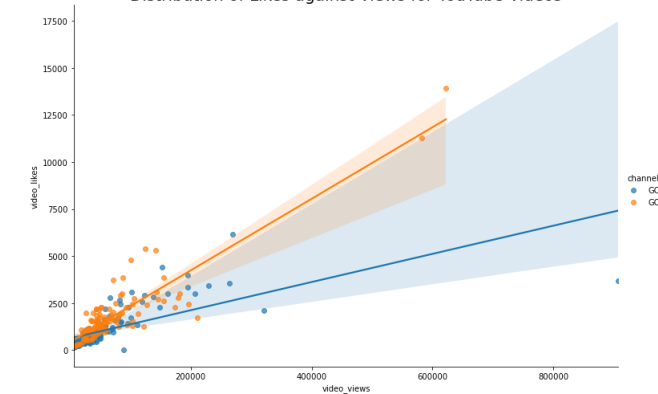


EDA – Instagram Posts

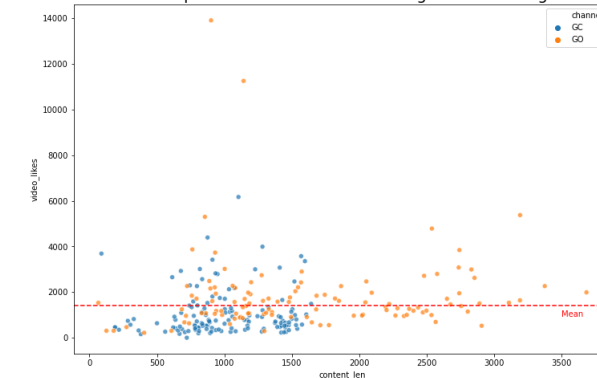
Distribution of Likes for YouTube Videos by Channels



Distribution of Likes against Views for YouTube Videos

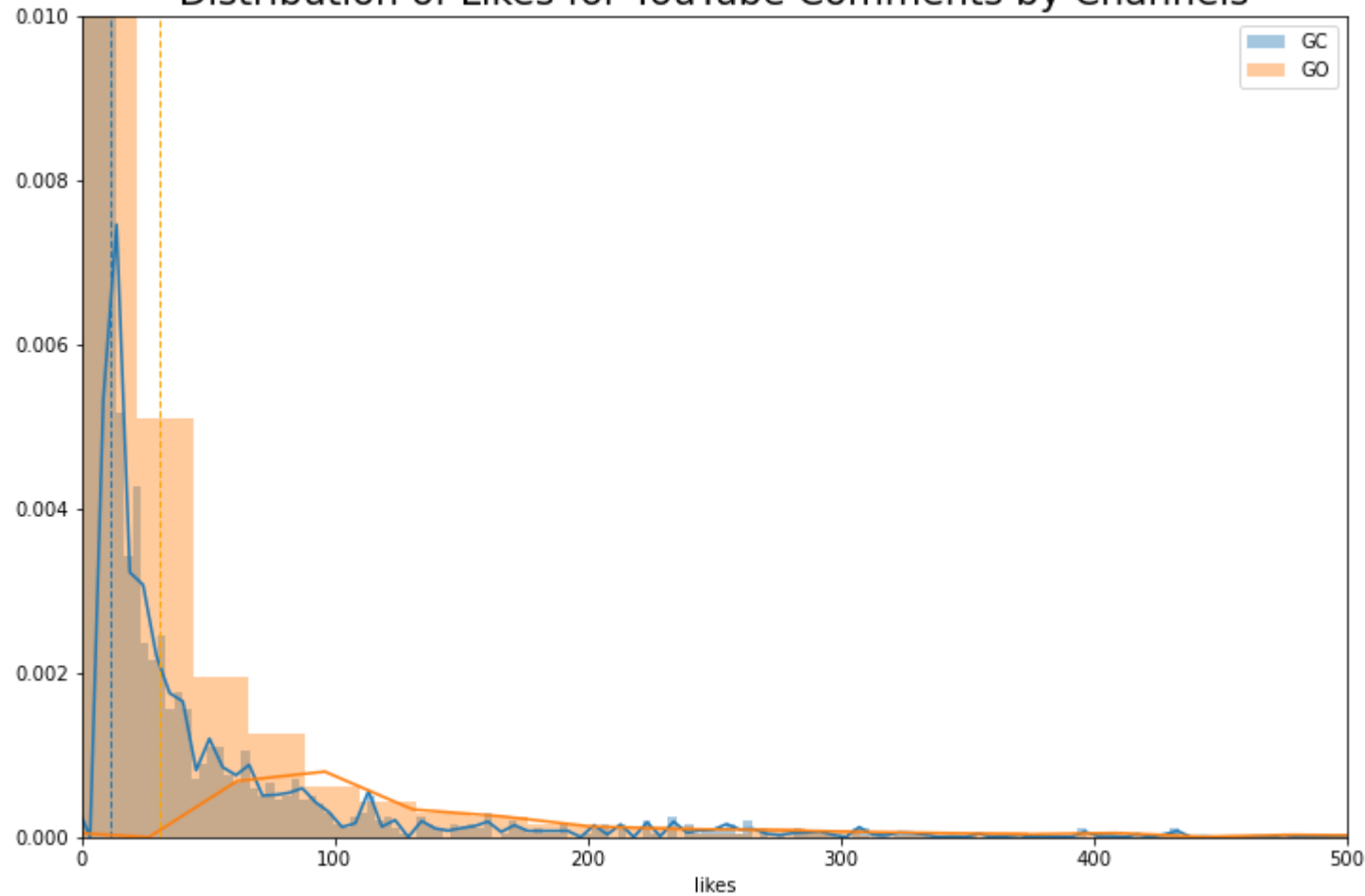


Scatter plot of YouTube Video Likes against Text Length

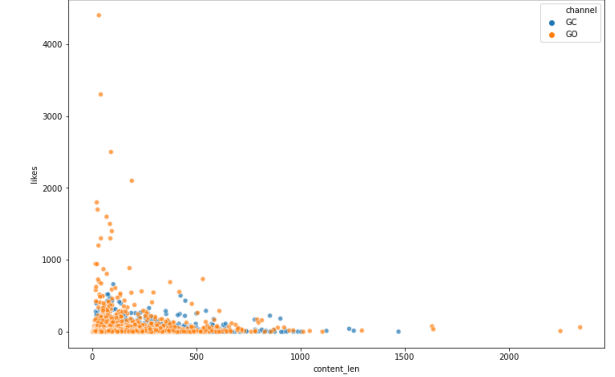


EDA – YouTube Videos

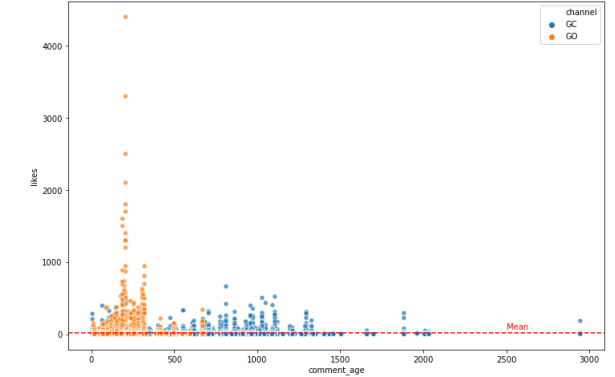
Distribution of Likes for YouTube Comments by Channels



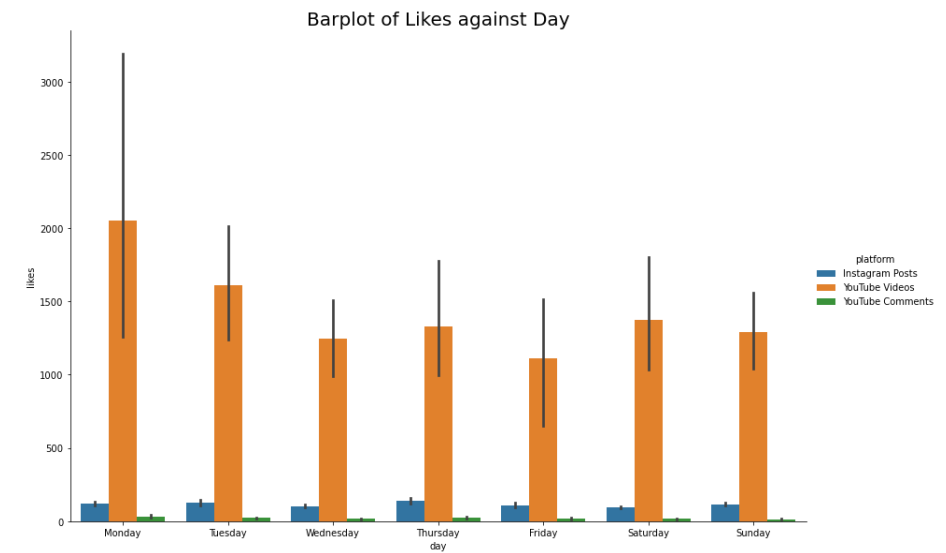
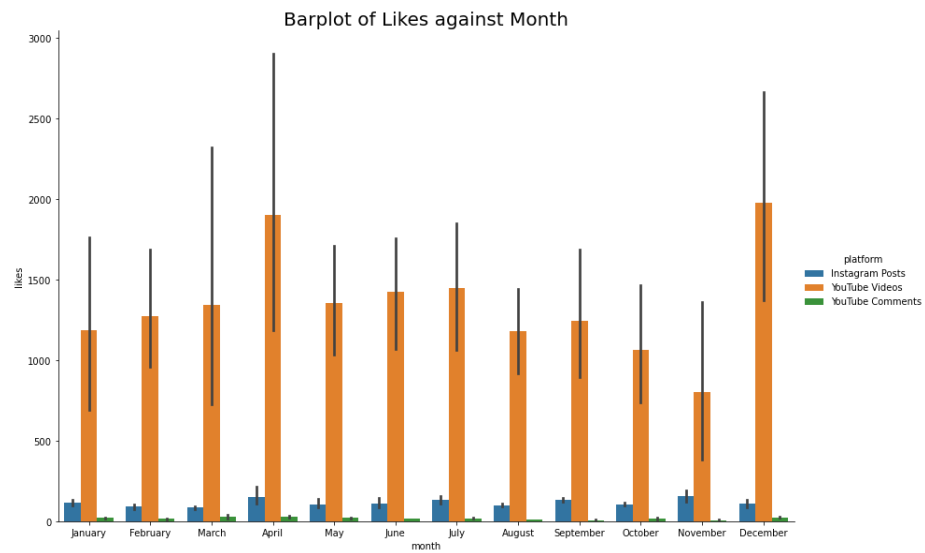
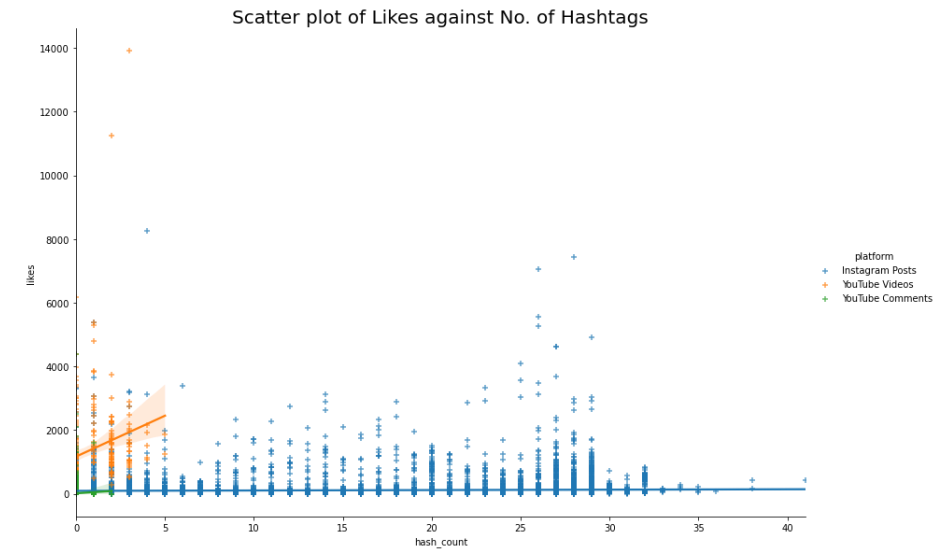
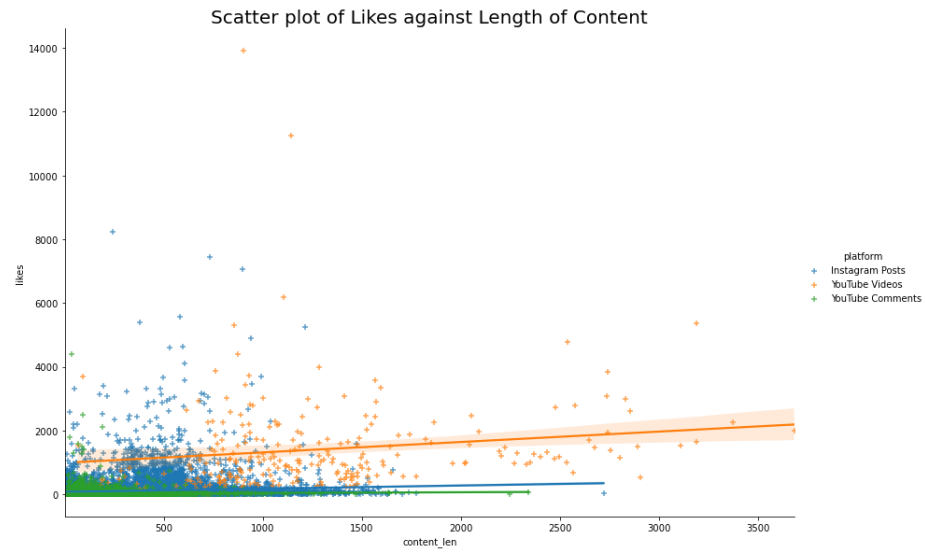
Scatter plot of YouTube Comment Likes against Text Length



Scatter plot of YouTube Comments Likes against Age



EDA – YouTube Comments



EDA – Overall

Modelling



Building and evaluating models.

Model	Cross-Validation Score (R^2)	Mean Squared Error	Validation Score Gap	Training Time (s)	Training Time (hh-mm-ss)
Ridge Regressor*	0.387	58557.4	-	70	1min 10s
Support Vector Regressor	-0.035	-	-	3022	50min 22s
Random Forest Regressor	0.401	-	-	5305	1h 28min 25s
Extra Trees Regressor	0.367	-	-	10306	2h 51min 46s
Ada-Boost Regressor	-7.124	-	-	2215	36min 55s
Gradient Boosting Regressor	0.363	-	-	587	9min 47s
XGBoost (gbtree, squared error) Regressor	0.303	-	-	158	2min 38s
XGBoost (gbtree, tweedie) Regressor	0.381	-	-	180	3min
XGBoost (gblinear, squared error) Regressor	0.398	-	-	41	41s
XGBoost (gblinear, tweedie) Regressor	0.317	-	-	36	36s
Feed-Forward NN	-	61421.0	18.1	28	28s
Feed-Forward NN (Ridge)	-	61419.7	596.5	27	27s
Feed-Forward NN (Lasso)	-	61259.4	541.3	27	27s
Recurrent NN (GRU)	-	101920.1	64157.1	1362	22min 42s
Recurrent NN (LSTM)	-	90009.7	33145.1	1270	21min 10s

Model Selection

Model	Optimised on	ROC-AUC	Accuracy	Recall	Specificity	Precision	F-1 Score
baseline*	-	-	0.709	-	-	-	-
Hybrid_01	ROC-AUC	0.727	0.734	0.711	0.743	0.532	0.609
Hybrid_02	F-1	0.731	0.735	0.724	0.739	0.533	0.614
Hybrid_03	SMOTE, F-1	0.719	0.699	0.765	0.672	0.489	0.597

Model	Optimised on	ROC-AUC	Accuracy	Recall	Specificity	Precision	F-1 Score
baseline*	-	-	0.709	-	-	-	-
NLP_01	ROC-AUC	0.713	0.716	0.706	0.721	0.509	0.592
nNLP_01	ROC-AUC	0.657	0.672	0.622	0.692	0.454	0.524
NLP_02	F-1	0.719	0.748	0.649	0.788	0.557	0.600
nNLP_02	F-1	0.669	0.648	0.717	0.620	0.437	0.543
NLP_03	SMOTE, F-1	0.688	0.674	0.721	0.655	0.462	0.563
nNLP_03	SMOTE, F-1	0.647	0.604	0.750	0.544	0.403	0.525

Built Models

Model	Optimised on	ROC-AUC	Accuracy	Recall	Specificity	Precision	F-1 Score
baseline*	-	-	0.709	-	-	-	-
Hybrid_01	ROC-AUC	0.727	0.734	0.711	0.743	0.532	0.609
Hybrid_02	F-1	0.731	0.735	0.724	0.739	0.533	0.614
Hybrid_03	SMOTE, F-1	0.719	0.699	0.765	0.672	0.489	0.597

	Predicted Negatives	Predicted Positives
Actual Negatives	3168	1097
Actual Positives	506	1246

Model 01

Model	Optimised on	ROC-AUC	Accuracy	Recall	Specificity	Precision	F-1 Score
baseline*	-	-	0.709	-	-	-	-
Hybrid_01	ROC-AUC	0.727	0.734	0.711	0.743	0.532	0.609
Hybrid_02	F-1	0.731	0.735	0.724	0.739	0.533	0.614
Hybrid_03	SMOTE, F-1	0.719	0.699	0.765	0.672	0.489	0.597

	Predicted Negatives	Predicted Positives
Actual Negatives	3168	1097
Actual Positives	506	1246

*False Positives,
Risk Resources*

Recall

*False Negatives,
Opportunity Cost*

Model 01

Model	Optimised on	ROC-AUC	Accuracy	Recall	Specificity	Precision	F-1 score
baseline*	-	-	0.709	-	-	-	-
Hybrid_01	ROC-AUC	0.727	0.734	0.711	0.743	0.532	0.609
Hybrid_02	F-1	0.731	0.735	0.724	0.739	0.533	0.614
Hybrid_03	SMOTE, F-1	0.719	0.699	0.765	0.672	0.489	0.597

	Predicted Negatives	Predicted Positives
Actual Negatives	3168	1097
Actual Positives	506	1246

*False Positives,
Risk Resources*

*False Negatives,
Opportunity Cost*

Precision

Model 01

Model	Optimised on	ROC-AUC	Accuracy	Recall	Specificity	Precision	
baseline*	-	-	0.709	-	-	-	-
Hybrid_01	ROC-AUC	0.727	0.734	0.711	0.743	0.532	0.609
Hybrid_02	F-1	0.731	0.735	0.724	0.739	0.533	0.614
Hybrid_03	SMOTE, F-1	0.719	0.699	0.765	0.672	0.489	0.597

F-1 score

	Predicted Negatives	Predicted Positives
Actual Negatives	3152 ⁻¹⁶	1113 ⁺¹⁶
Actual Positives	484 ⁻²²	1268 ⁺²²

Model 02

Model	Optimised on	ROC-AUC	Accuracy	Recall	Specificity	Precision	F-1 score
baseline*	-	-	0.709	-	-	-	-
Hybrid_01	ROC-AUC	0.727	0.734	0.711	0.743	0.532	0.609
Hybrid_02	F-1	0.731	0.735	0.724	0.739	0.533	0.614
Hybrid_03	SMOTE, F-1	0.719	0.699	0.765	0.672	0.489	0.597

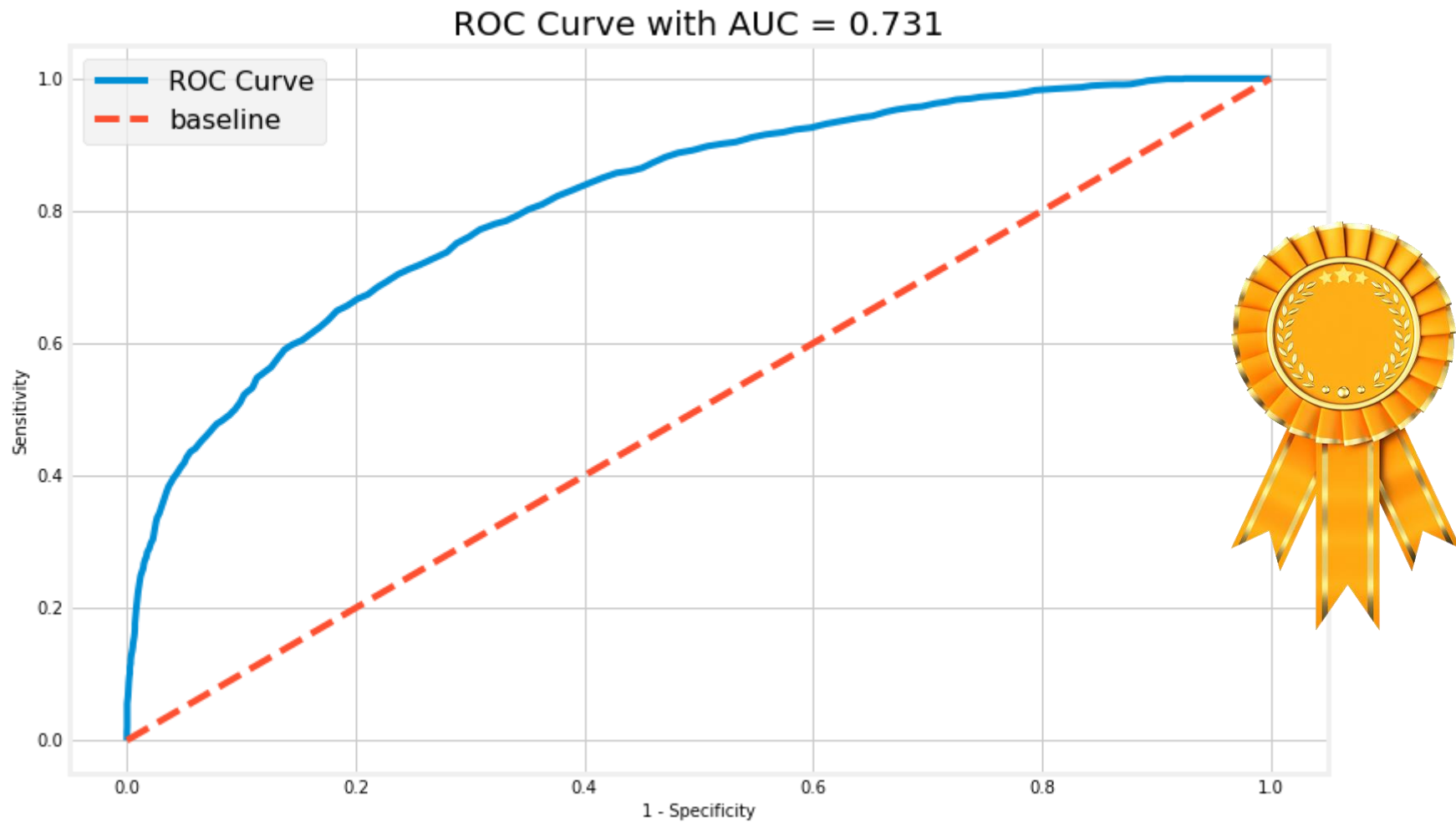
	Predicted Negatives	Predicted Positives
Actual Negatives	3152 ⁻¹⁶	1113 ⁺¹⁶
Actual Positives	484 ⁻²²	1268 ⁺²²

*False Positives,
Risk Resources*

*False Negatives,
Opportunity Cost*

Precision

Model 02



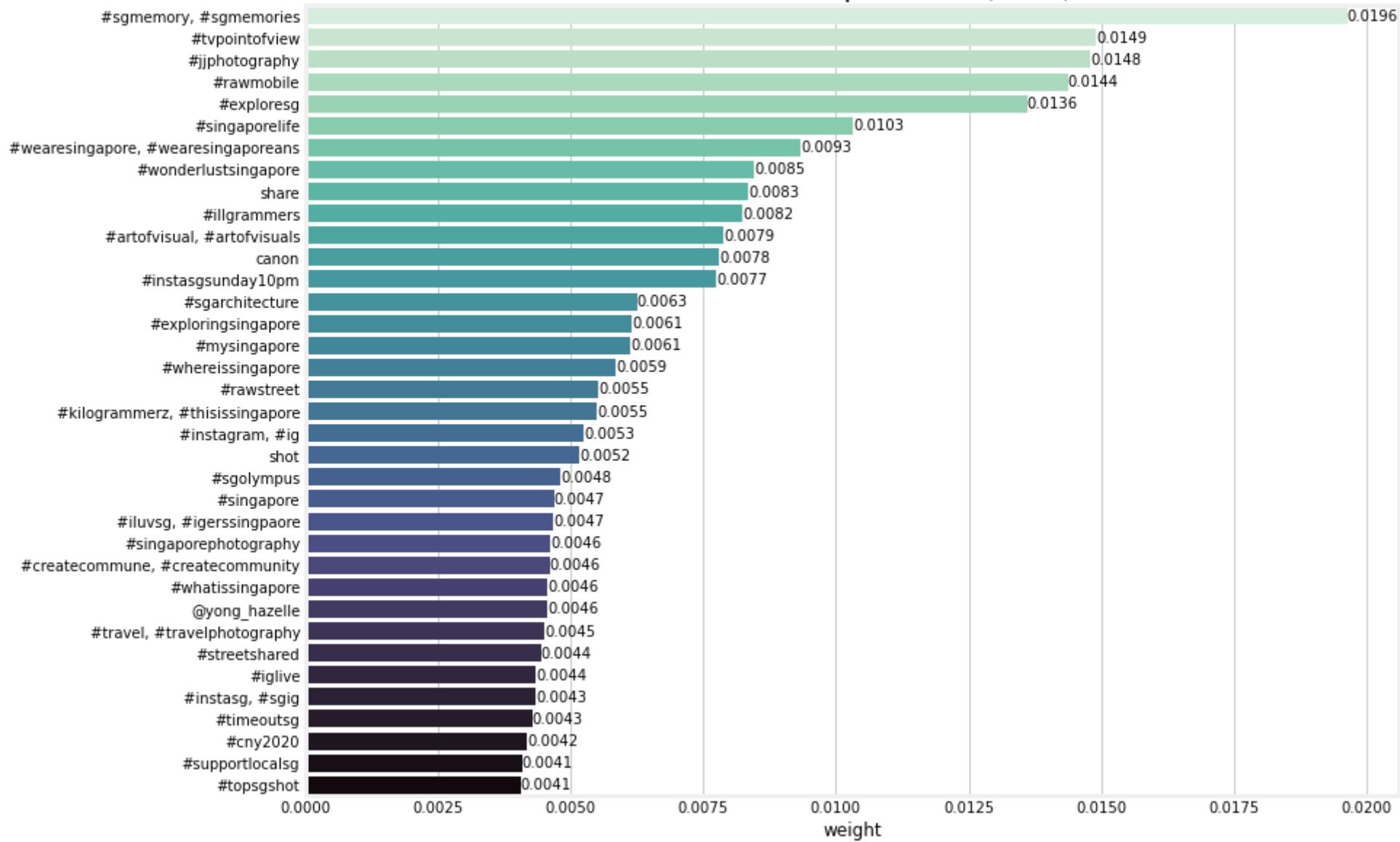
Model 02

Inference



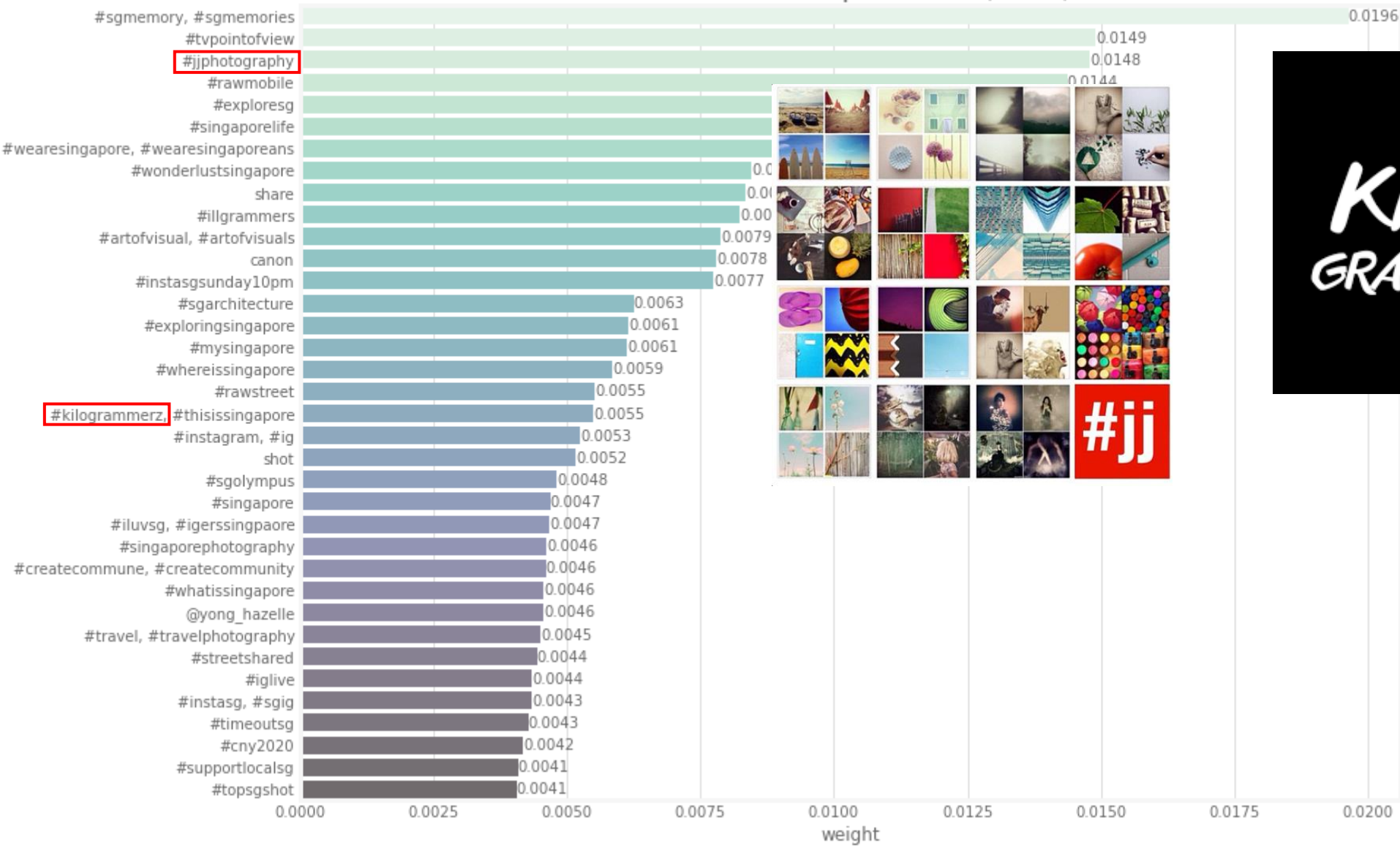
Inferring and extracting insights from model.

Plot of NLP Features Importance (Gain) > 0.004



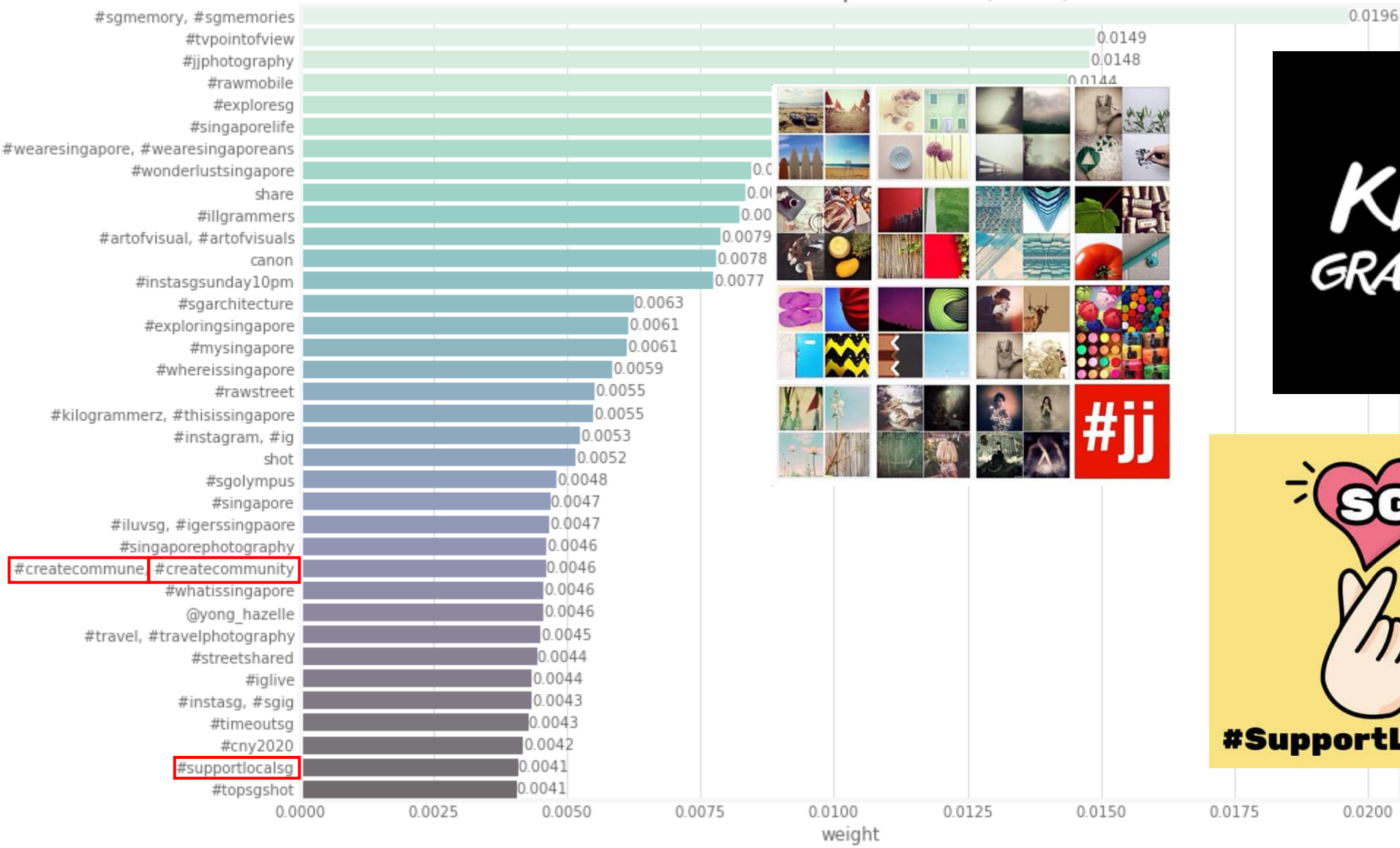
Model 02 – NLP

Plot of NLP Features Importance (Gain) > 0.004



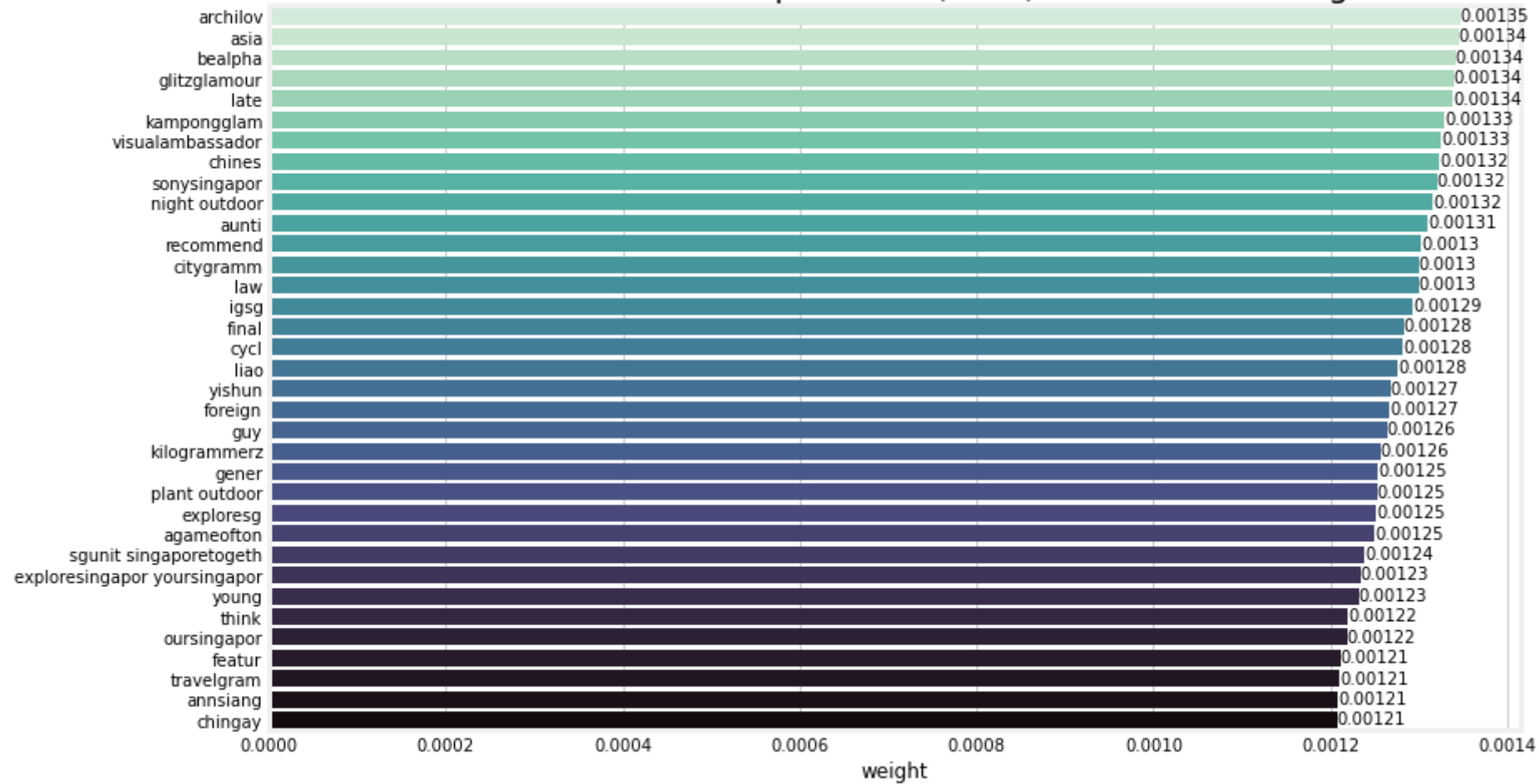
Model 02 – NLP

Plot of NLP Features Importance (Gain) > 0.004



Model 02 - NLP

Plot of NLP Features Importance (Gain) with Smaller Weights



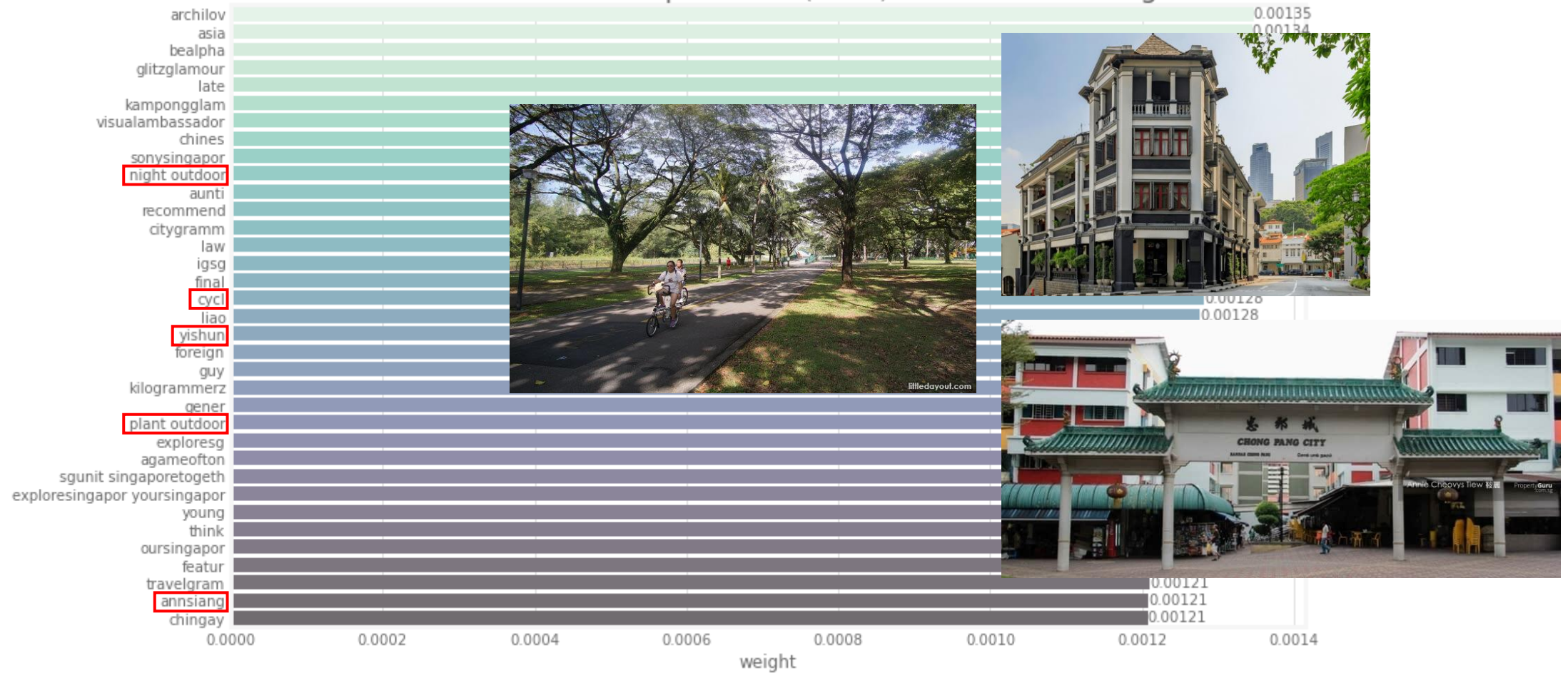
Model 02 – NLP

Plot of NLP Features Importance (Gain) with Smaller Weights



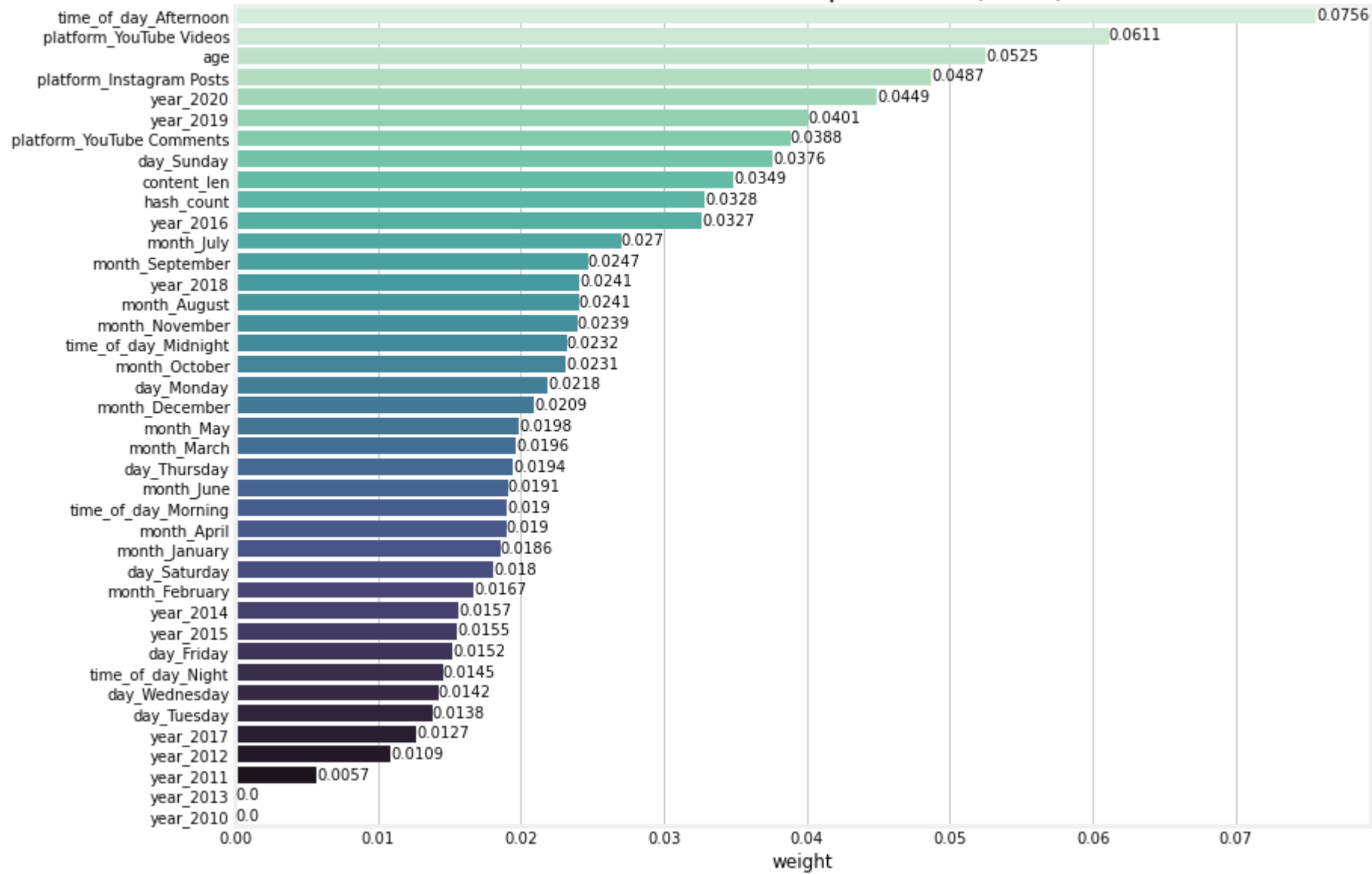
Model 02 – NLP

Plot of NLP Features Importance (Gain) with Smaller Weights



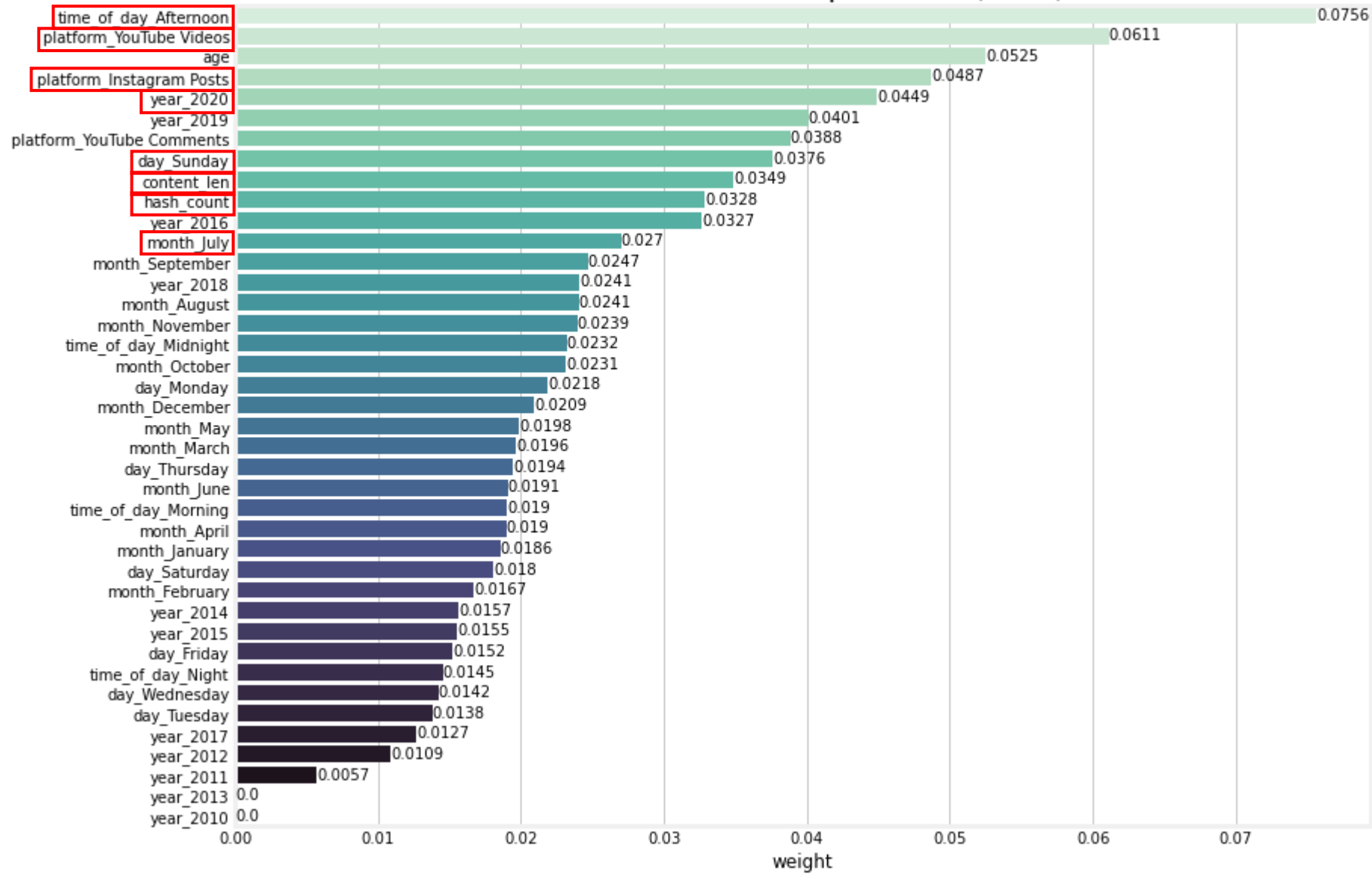
Model 02 – NLP

Plot of non-NLP Features Importance (Gain) > 0.004



Model 02 – non-NLP

Plot of non-NLP Features Importance (Gain) > 0.004



Model 02 – non-NLP

Actionables

Recommendations based on insights for the next phase of #SingapoRediscovered campaign.

Instagram Photo Cycle



Proposal 01

Instagram Photo Cycle



Proposal 01

Instagram Photo Cycle

"I just went on #STB photo cycle challenge in Singapore's most dangerous neighbourhood, Yishun. It was easy cycling along the park connector, and I was able to make pitstops along the way and just enjoy the nature. Check out this beautiful temple I came across in the middle of the HDB estate. Who knew? I am looking forward to lunch now.

#exploresg #wonderlustsingapore #singaporediscovers #photocycle #photocycling #sgbike #kilogrammerz #supportlocalsg"



Proposal 01

Instagram Photo Cycle

"I just went on #STB photo cycle challenge in Singapore's most dangerous neighbourhood, Yishun. It was easy cycling along the park connector, and I was able to make photos along the way and just enjoy the nature. Check out this beautiful temple I came across in the middle of the 4500 estate. Who knew? I am looking forward to lunch now.

59.0%

#exploresg #wonderlustsingapore #singaporediscovers #photocycle #photocycling #sgbike #kilogrammerz #supportlocalsg"

Proposal 01

Pseudo-Travel in Singapore



Proposal 02

Pseudo-Travel in Singapore



Proposal 02

Pseudo-Travel in Singapore

"Visiting the Thailand of Singapore - Golden Mile Complex

Did you know there is Little Thailand in Singapore? Today, I visited Golden Mile Complex at Beach Road. It's a mall with over 400 retail shops and restaurants where the local Thai community hangs out. Here, you are instantaneously transported to Thailand. Join me on today's journey of Golden Mile Complex in Singapore.

#Singapore #GoldenMileComplex"



Proposal 02

Pseudo-Travel in Singapore

"Visiting the Thailand of Singapore - Golden Mile Complex

Did you know there is Little Thailand in Singapore? That's the United Golden Mile Complex at Beach Road. It's a mall with over 400 retail shops and restaurants where the local Thai community hangs out. Here, you are instantaneously transported to Thailand. Join me on today's journey of Golden Mile Complex in Singapore.

#Singapore #GoldenMileComplex"

56.7%

Proposal 02

Chingay behind-the-scenes YT mini-series



Proposal 03

Chingay behind-the-scenes YT mini-series



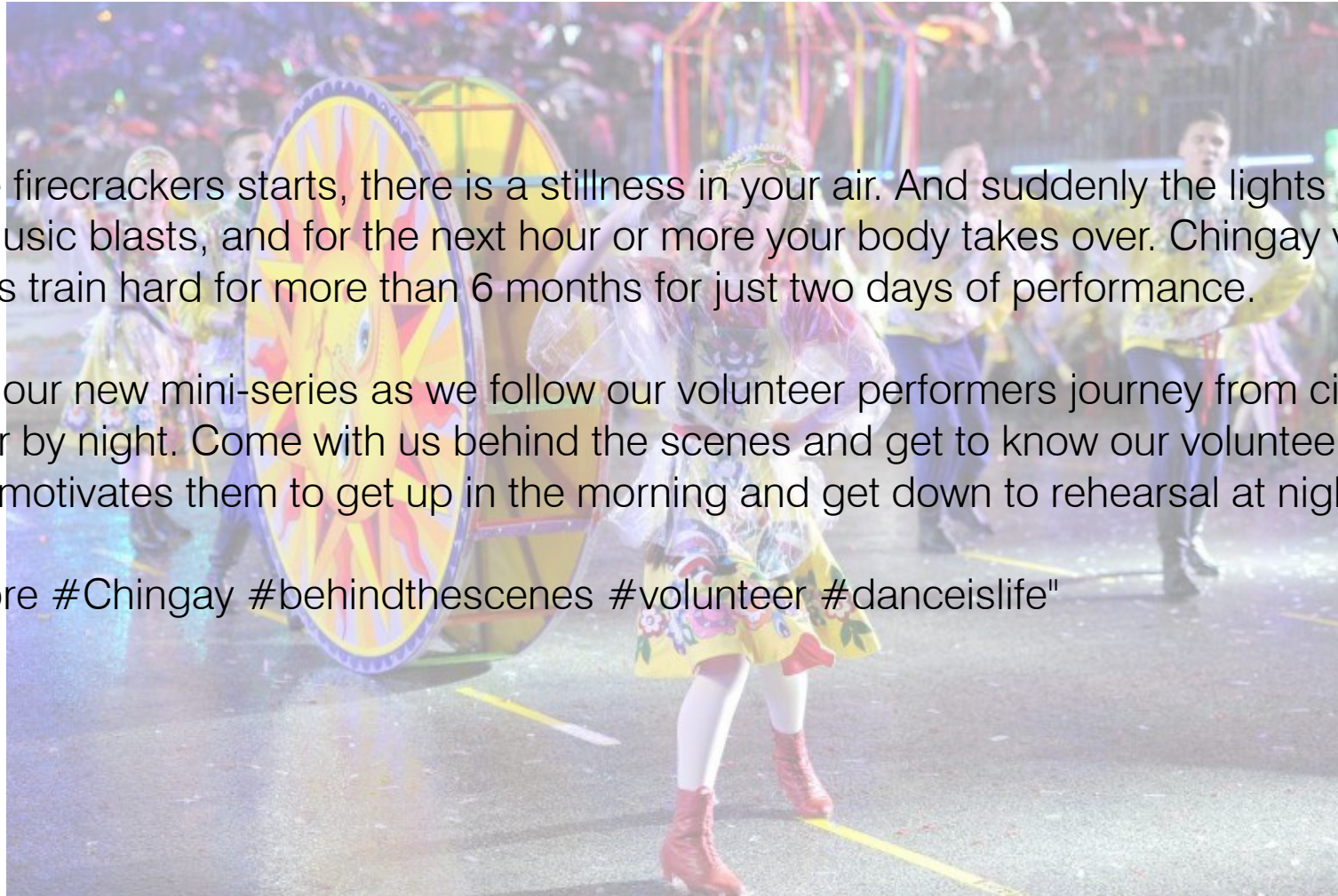
Proposal 03

Chingay behind-the-scenes YT mini-series

"When the firecrackers starts, there is a stillness in your air. And suddenly the lights come on, and the music blasts, and for the next hour or more your body takes over. Chingay volunteer performers train hard for more than 6 months for just two days of performance.

Join us in our new mini-series as we follow our volunteer performers journey from citizen in the day to star by night. Come with us behind the scenes and get to know our volunteer performers, and what motivates them to get up in the morning and get down to rehearsal at night.

#Singapore #Chingay #behindthescenes #volunteer #danceislife"



Chingay behind-the-scenes YT mini-series

"When the firecrackers starts, there is a stillness in your air. And suddenly the lights come on, and the music blasts, and for the next hour or more your body takes over. Chingay volunteer performers train hard for more than 6 months for just two days of performance.

Join us in our new mini-series as we follow our volunteer performers journey from citizen in the day to star by night. Come with us behind the scenes and get to know our volunteer performers, and what motivates them to get up in the morning and get down to rehearsal at night.

#Singapore #Chingay #behindthescenes #volunteer #danceislife"

Proposal 03

Moving Forward



What's next?

What more can be done?

Our model has some **limits** which we can try to overcome:

- By gathering more data
- Trying a weighted form of aggregation
- Dropping all hashtags if enough data is acquired to offset information loss
- Building a Flask app to deploy the model
- Image modelling or transcribing videos to directly access the content

What's Next?

Any Questions?



Thank you for your attention!