What makes the area surrounding MRT stations in Singapore look Beautiful, Safe & Welcome?

PREPARED BY: TEAM DUO (LEE WAN NING, ANDREA YIAP)

Introduction

What makes the area surrounding MRT stations in Singapore look Beautiful, Safe & Welcome?


THE STRAITS TIMES

Singapore is most beautiful city in Asia, 11th most beautiful in the world


THE STRAITS TIMES

Singapore is world's second safest city, after Tokyo, in EIU's Safe Cities Index


THE STRAITS TIMES

Singapore is world's most welcoming city for tourists: Travel index

Leveraging Image Analysis and crowdsourcing

To understand public perceptions on “What makes the area surrounding MRT stations in Singapore look *Beautiful*, *Safe*, and *Welcome*?”

BACKGROUND

- Inspired by the research paper **“Aesthetic Capital: What makes London looks Beautiful, Quiet and Happy?”** published by Yahoo Labs in 2014

- Complement the past urban perception studies done in Singapore which focuses on other aspects such as **heritage**, **tourism**, **green and sustainability** initiatives

BACKGROUND

Why “Beautiful”, “Safe” and “Welcome” ?

- Multiple studies: **“Beautiful”** as a common and important indicator of a desirable city
- **Safety** is fundamental to the development and growth of cities
- **Welcoming** cities often associated with tourism

Focusing on the perspectives of people living in Singapore, whose perspectives towards these metrics matter the most.

How we define “Beautiful”, “Safe” and “Welcome”?

- **Beautiful** refers to the aesthetic of the place, the structure of the buildings/ greenery that makes the place looks astounding
- **Safe** refers to the environment of the place, where you feel safe to walk without any fear
- **Welcome** refers to the place making you feel invited and comfortable, somewhere where you are willing to stay for awhile longer (assuming you are not busy and don't have anywhere to go)

BACKGROUND

Why MRT stations?

- Starting point used in the **2014 London reference research paper**
- Reasonable to **represent Singapore** as a whole due to its dense and widespread distribution
- Narrow the scope to **only MRT stations** for ease of data collection, processing and analysis

Project Overview

Project Objective

To quantify the Singapore public's perceptions towards MRT stations and its surroundings on the qualities of "Beautiful", "Safe" and "Welcome"

220 MRT images → Each respondent rate 10 random MRT images based on the 3 qualities → Conduct Data Processing → Perform Image Analysis Techniques → Prepare Survey Results & Image Insights

Perform Image Analysis Techniques:
- Colours
- Bag of Visual Words
- Object Detection

- IRB Approved
- 231 Respondents

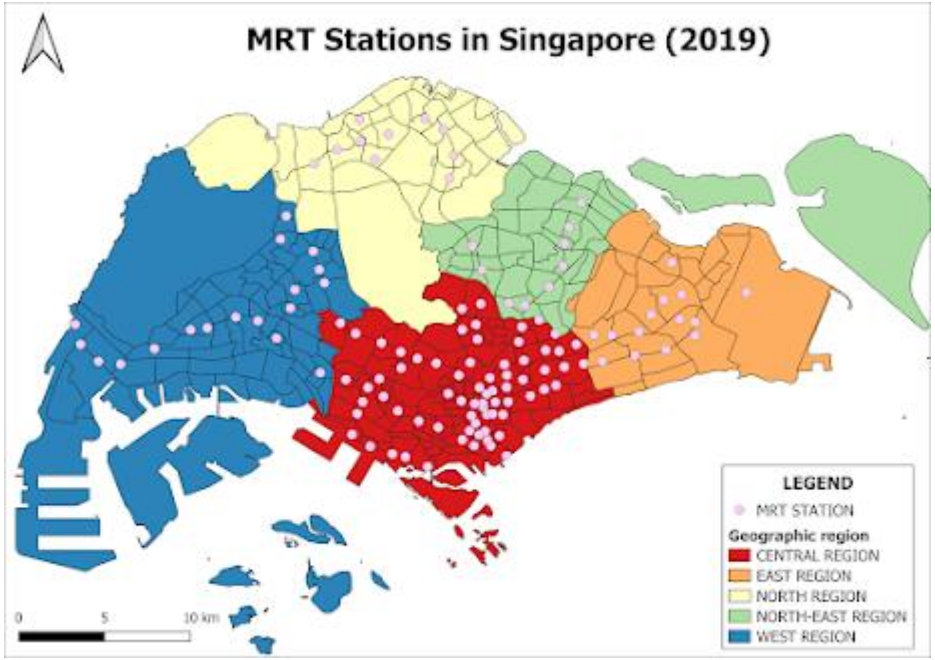
Expected Outcome

To discover the visual elements that defines the qualities of "Beautiful", "Safe" and "Welcome in the eyes of the Singapore public

Project Sponsor: [redacted]
Project Supervisor: [redacted]

DATA COLLECTION & PROCESSING

MRT STATIONS DATA



How we retrieve **MRT stations data**?

- Obtained data from open-sourced platform, data.gov.sg provided by LTA
- Data is in .shp/.xml file format

How we process **MRT stations data**?

- Process MRT stations data using open-sourced geospatial software, **QGIS**
- Remove duplicates and non-operational MRT stations
- Extract latitude and longitude values for each MRT station

Outcome

Obtain pairs of latitude and longitude geographic coordinates for 122 MRT stations in Singapore

MRT STATIONS IMAGES DATA

Google Street images centered around Promenade MRT station

0/360 degrees

90 degrees

180 degrees

270 degrees

How we **collect** MRT and the areas surrounding it **images**?

Retrieve outdoor images of areas surrounding MRT stations (300m radius) using **Google Street View API**, with the latitude and longitude coordinates as inputs

- 1 pair of lat/lon coordinates = 1 image returned Google Street View API
- 4 images (4 different angles) per MRT station (each pair of lat/long coordinates)

Google Street View API (Google map services)

- Massive collection of street-level images, which closely resembles actual landscape from a person's point of view
- Consistent image quality

Outcome
Obtain 488 images from 122 MRT stations

MRT STATIONS IMAGES DATA





How we **filter out** unwanted MRT images?

Criteria

- Old images (by images' date of captures, reject those taken before 2018
- Indoor/hybrid indoor images
- Huge objects blocking/affecting > 50% the view (E.g advertisement boards, trucks)
- Blurred images (areas censored by Google API)

Purpose of filtering out unwanted MRT images:

- To ensure the MRT images are clean and not corrupted

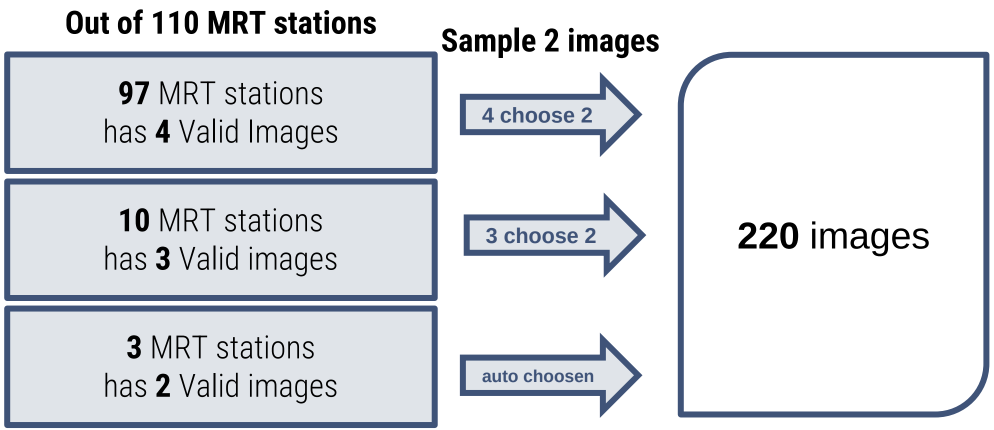
Outcome
427 valid images from 113 MRT stations 97 MRT stations with 4 images each 10 MRT stations with 3 images each 3 MRT stations with 2 images and 1 images each respectively

MRT STATIONS IMAGES DATA

How we **choose the images** after filtering out the unwanted images to be used for our Survey?

Perform **simple random sampling** of MRT images to reduce selection bias due to **unequal number of images** per MRT stations after filtering

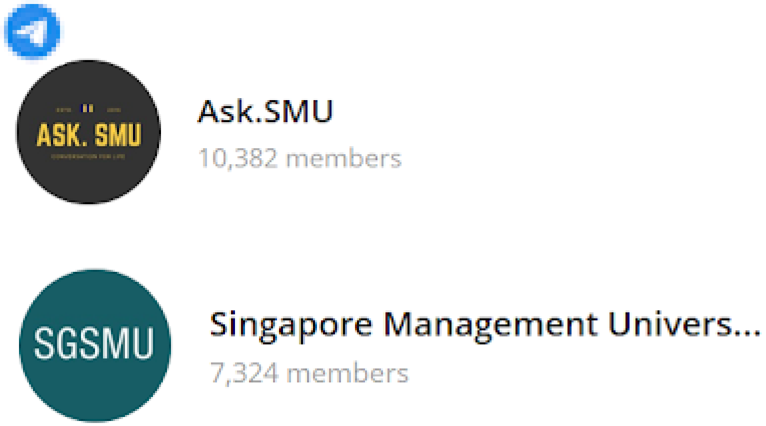
- Random select **2 images** from each MRT stations that have **at least 2 valid images** using python's random.sample

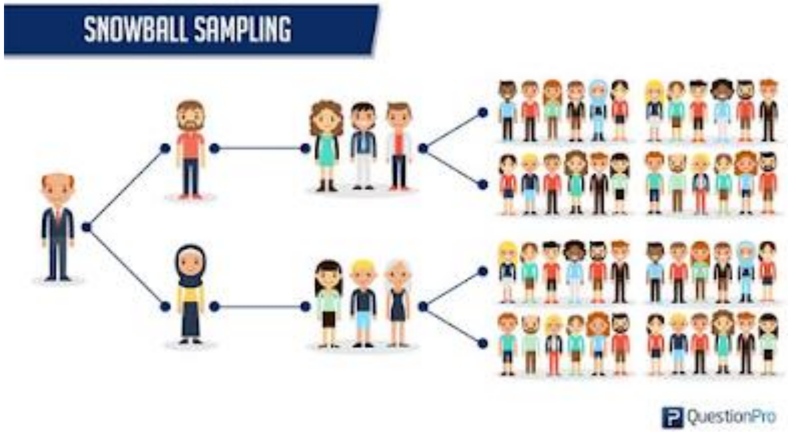


Outcome

220 images from 110 MRT stations

IMAGES PERCEPTION DATA





Details on our Survey:

- Survey platform: **Qualtrics** to crowdsource perceptions on MRT images
- Target audience: **SMU community and their social networks**
- Target survey respondents : **200**
- Survey is **IRB approved**

Survey distribution

- **Convenience sampling** via social media platforms like telegram and class announcements (Prof [redacted])
- **Snowball sampling** where survey participants recruit more participants through their social connections via word-of-mouth
- Survey incentives : $5 Grab transport voucher

Expected Outcome:

At least 200 survey responses

IMAGES PERCEPTION DATA

Format of survey

- **Demographics** questions (Gender, Age, Nationality)
- **10 image perception** questions
  - Each question contain **1 image** and **3 metrics** (Beautiful,Safe,Welcome)
  - Respondents have to rate the image for each metric on a **scale of 1 (Strongly disagree) to 5 (Strongly agree)**
  - **10 images** will be **randomly selected** out of 220 MRT images for display to each survey respondent

Expected Outcome:

At least 200 survey responses

To ensure **validity** of the images perception data,

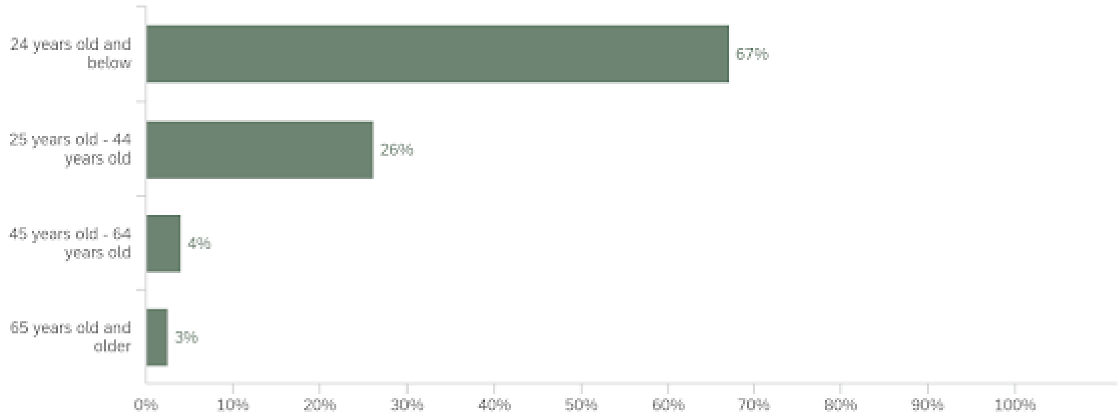
✓ **Ensure no respondents speeding through Survey**

SURVEY RESULTS

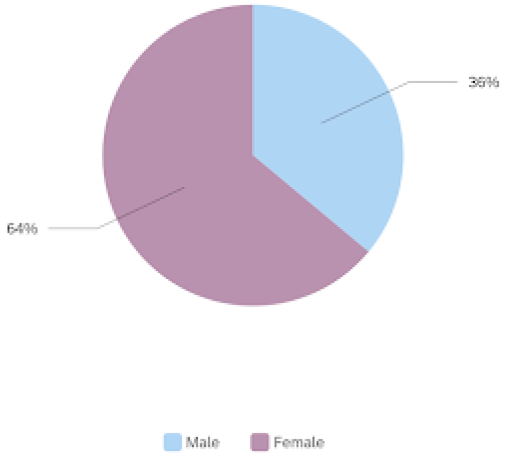
Descriptive statistics

231 survey respondents

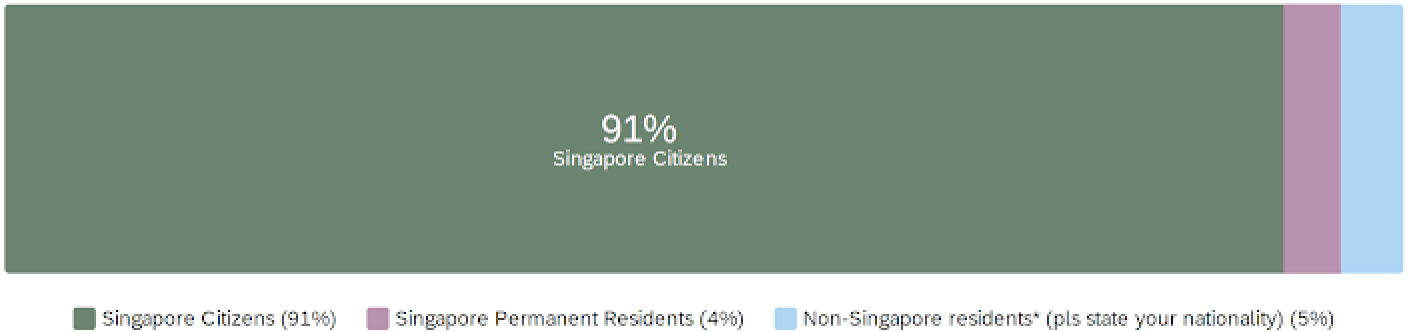
Age Graph



Gender Graph



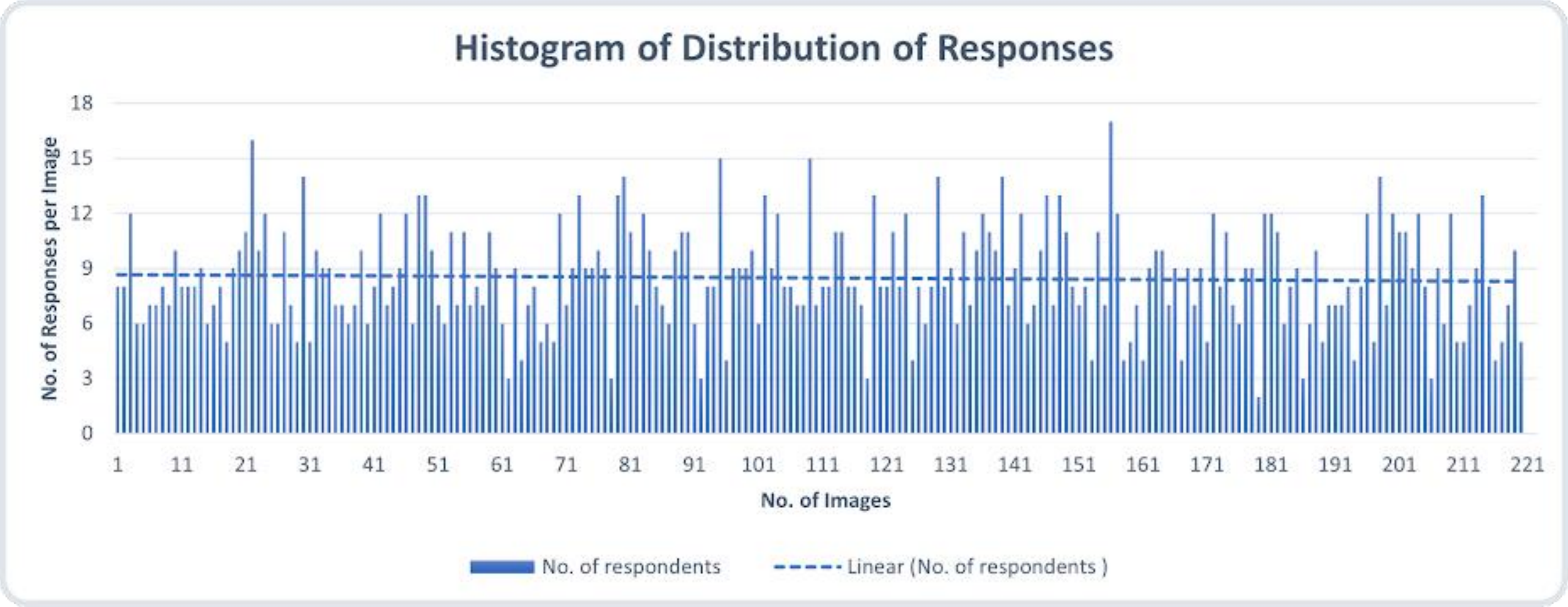
Nationality Graph



220 survey images

Average (**median**): **8 responses** per image
(**minimum**): **2 responses** per image
(**maximum**): **17 responses** per image

*Total images: **220**



VALIDITY OF SURVEY

Did the survey respondents speed through our survey?

Median time taken for each person to finish each image rating qn: **10.346 seconds**

All but **1 survey respondents sped** through our survey, this implies that our survey data on image perceptions are validated

All 231 survey responses pertaining to image perceptions will be used in our survey result and image analysis

Ranking of MRT images

Compute the Median ratings for each of the 3 metrics for each of the 220 images

Ranking of MRT stations

Add up the median ratings for each of the 3 metrics for images belonging to the same MRT station

SURVEY RESULTS

Based on overall median ratings for each of the 110 MRT stations

Overall

Most **beautiful** MRT stations and its surroundings

CITY HALL MRT STATION

RAFFLES PLACE MRT STATION

Least **beautiful** MRT stations and its surroundings

ANG MO KIO MRT STATION

SERANGOON MRT STATION

Insights

- **Beautiful images tend to contain greenery**
- **Unbeautiful images tend to contain trucks and bicycles**

Overall

Most **safe** MRT stations and its surroundings

CHINESE GARDEN MRT STATION

YIO CHU KANG MRT STATION

Least **safe** MRT stations and its surroundings

PUNGGOL MRT STATION

BISHAN MRT STATION

Insights

- Safe images tend to contain sheltered walkways
- Unsafe images tend to contain trucks, vans and lorries

Overall

Most **welcome** MRT stations and its surroundings

TIONG BAHRU MRT STATION

UPPER CHANGI MRT STATION

Least **welcome** MRT stations and its surroundings

SERANGOON MRT STATION

BISHAN MRT STATION

Insights

- **Welcoming images tend to contain greenery and houses**
- **Unwelcoming images tend to contain dull and greyish colour tones and trucks**

SURVEY RESULTS

Inferential Statistics

DEMOGRAPHIC DIFFERENCES

Is there are any **difference** in the **mean of images ratings** for each metrics due to demographics differences in our survey respondents?

Paired T-test Result				
Metrics	**Demographic (Gender)**	**P-value**	**Demographic (Age)**	**P-value**
Beautiful	Female 3.14 +- 0.81	0.255	24 years and below 3.25 +- 0.82	0.133
	Male 3.21 +- 0.90		25 years old-44 years old 3.15 +- 0.89	
Safe	Female 3.44 +- 0.70	0.491	24 years and below 3.50 +- 0.73	0.209
	Male 3.4 +- 0.78		25 years old-44 years old 3.43 + -0.71	
Welcome	Female 3.15 +- 0.72	0.025	24 years and below 3.24 +- 0.75	0.290
	Male 3.29 +- 0.83		25 years old-44 years old 3.18 +- 0.80	

Paired-test applied only on images ratings from 210 images for **Gender**

Paired-test applied only on images ratings from 195 images for **Age**

P-value <= 0.05 :
difference in the mean of images ratings due to demographic differences is **statistically significant** at 5% significance level

Insights

There is gender difference in perceiving welcomeness of an image

IMAGE ANALYSIS

Based on overall median ratings on each of the 220 images

IMAGE ANALYSIS

COLOURS

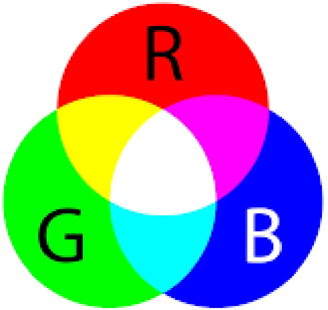
Based on overall median ratings on each of the 220 images

COLOURS

Perform linear regression to find out the effects of colors on image perception ratings for each of the 3 metrics (Beautiful,Safe, Welcome)

How and What colors are extracted and tested on?

- Extract average redness, blueness and greenness(based on the RGB color model) from each image for all 220 images using **skimage image processing python package**



Why RGB color model to represent colors?

1. Most well-known and **common representation** of colors
2. **Simple** to understand
    a. Different intensities and combinations of the 3 primary colors (Red, Green,Blue) add up to give rise to different colors
    b. Color intensity ranges from 0 to 255 for each of the 3 primary colors

Outcome

Obtained average redness, greenness and blueness values from each of the 220 images

COLOURS

P-value <= 0.05 means that the effect of the color in the images on the image ratings given is **statistically significant** at 5% significance level

(highlighted in green fill)

R-squared:
How well these 3 colors explain the change in image ratings, assuming a linear relationship exists

Linear Regression Result
Image ratings =Average Redness +Average Greenness + Average Blueness + Constant

	Dependent variable	Independent variables						R-squared
	Image ratings	Avg_R	P-value	Avg_G	P-value	Avg_B	P-value	
Image metrics	Beautiful	-0.0569	0.000	0.0696	0.000	-0.0107	0.176	0.102
	Safe	0.0002	0.984	0.0085	0.534	-0.0046	0.488	0.016
	Welcome	-0.0191	0.105	0.0312	0.032	-0.0093	0.192	0.029

Insights

- **Greater average greenness in images lead to higher beautiful and welcome image ratings**
- **Greater average redness in images lead to lower beautiful image ratings**
- **These 3 primary colors alone are insufficient in explaining the changes in image ratings**

COLOURS

Perform a more **refined linear regression** to find out the effects of colors on image perception ratings for each of the 3 metrics (**Beautiful**, **Safe**, **Welcome**)

- Increase the **number and variation of colors** used in the linear regression model

How and what colors are extracted and tested on?

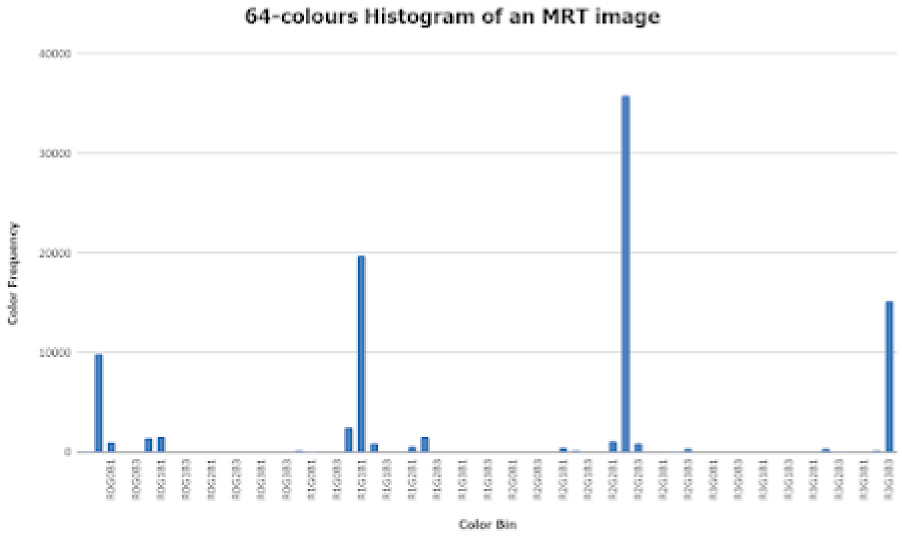
Part 1: **Condense all possible colors into 64 colors (color bins) based on RGB color model**

Color intensities split into 4 range

COLOURS

Perform a more **refined linear regression** to find out the effects of colors on image perception ratings for each of the 3 metrics (**Beautiful**, **Safe**, **Welcome**)

- Increase the **number and variation of colors** used in the linear regression model



How and what colors are extracted and tested on?

Part 2: **Compute the 64-colors histogram**

a. Compute the **frequencies** of each color in each image for all 220 images

b. **Max color frequency** = 94376 = **total number of image pixels** in an image (with dimensions of 251 in width x 376 in height)

Outcome

Obtained counts for 53 colors in each of the 220 images

(remaining 11 colors are not present in any of the 220 images)

COLOURS

Perform **correlation analysis** (Pearson's correlation) to select the colors that have a strong linear relationship with image perception ratings for each of the 3 image metrics(**Beautiful**, **Safe**, **Welcome**)

- Strong correlation value set at >0.15 or <-0.15 (referenced from the London paper)

Strong correlated color bins, ordered in descending order (from left to right)

Beautiful	R2G2B3	R1G0B0	R1G1B1	R1G2B0	R1G2B2	R1G2B1	R1G1B2	R3G2B2
	Light blue-magneta	Dark red	Dark gray	Dark green	Cyan	Green	Blue-magneta	Light red

Safe	R3G1B2	R1G2B0	R3G3B0	R3G2B0	R3G3B1
	Light pink	Dark green	yellow-green	yellow	Light yellow-green

Welcome	R3G2B2	R2G2B3	R0G2B2	R1G1B1	R2G0B1	R3G1B2
	Light red	Light blue-magneta	Dark cyan	Dark gray	pink	Light pink

Outcome

8, 5, 6 color bins for Beautiful, Safe and Welcome respectively

Insights

Light blue-magneta, dark green, light pink and cyan tend to have strong effects on Beautiful, Safe and Welcome qualities of images

COLOURS

R-squared value: 0.163

Signifies how well these colors explain the change in image ratings, assuming a linear relationship exists

Refined Linear Regression Result
Image ratings = strongly correlated colors + Constant

Dependent variable	Independent variables (colors)							
Image ratings (**Beautiful**)	**Light blue-magneta**	**Dark red**	**Dark gray**	**Dark green**	**Cyan**	**Green**	**Blue-magneta**	**Light red**
	0.00005	-0.00007	-0.00001	0.00020	0.00006	0.00009	0.00004	0.00004
P-value	0.141	0.393	0.281	0.13	0.118	0.196	0.006	0.348

P-value <= 0.05 means that the effect of the color in the images on the image ratings given is **statistically significant** at 5% significance level

(highlighted in green fill)

Insights

- More blue-magneta color in images lead to higher beautiful image ratings
- These 8 colors alone are insufficient in explaining the changes in image ratings

COLOURS

These images contain high counts of **blue-magneta** which is highly correlated with beautiful images

PROMENADE MRT STATION

BUGIS MRT STATION

BUONA VISTA MRT STATION

Blue-magneta

COLOURS

R-squared value: 0.098

Signifies how well these colors explain the change in image ratings, assuming a linear relationship exists

Refined Linear Regression Result Image ratings = strongly correlated colors + Constant					
Dependent variable	Independent variables (colors)				
Image ratings (Safe)					
	Light pink	**Dark green**	**yellow-green**	**yellow**	**Light yellow-green**
	-0.0233	0.0002	-0.0011	-0.0013	-0.0005
P-value	0.013	0.013	0.283	0.861	0.135

P-value <= 0.05 means that the effect of the color in the images on the image ratings given is **statistically significant** at 5% significance level

(highlighted in green fill)

Insights

- **More light pink color in images lead to lower safe image ratings**
- **More dark green color images lead to higher safe image ratings**
- **These 5 colors alone are insufficient in explaining the changes in image ratings**

COLOURS

These images contain high counts of **light pink** which is highly correlated to less safe images

CLEMENTI MRT STATION

UBI MRT STATION

BISHAN MRT STATION

Light pink

COLOURS

These images contain high counts of dark green which is highly correlated to safer images

DAKOTA MRT STATION

BUKIT BATOK MRT STATION

TAMPINES EAST MRT STATION

Dark green

COLOURS

R-squared value :
0.123

Signifies how well these colors explain the change in image ratings, assuming a linear relationship exists

Refined Linear Regression Result Image ratings = strongly correlated colors + Constant						
Dependent variable	Independent variables (colors)					
Image ratings (Welcome)	**Light red**	**Light blue-magneta**	**Dark cyan**	**Dark gray**	**pink**	**Light pink**
	0.00007	0.00002	-0.01590	-0.00001	- 0.00110	-0.01510
P-value	0.007	0.241	0.128	0.113	0.15200	0.07

P-value <= 0.05 means that the effect of the color in the images on the image ratings given is **statistically significant** at 5% significance level

(highlighted in green fill)

Insights

- **Greater light red color in images lead to higher welcome image ratings**
- **These 6 colors alone are insufficient in explaining the changes in image ratings**

COLOURS

These images contain high counts of **light red**, which is highly correlated with welcoming images

BEDOK NORTH MRT STATION

UPPER CHANGI MRT STATION

BOON KENG MRT STATION

Light red

IMAGE ANALYSIS

OBJECT DETECTION

Based on overall median ratings on each of the 220 images

OBJECT DETECTION

Use **correlation analysis (Pearson's correlation)** to find out the association between objects and image perception ratings for each of the 3 metrics (Beautiful,Safe, Welcome) for each of the 220 images

The object detection model can detect cars, traffic lights, trucks, persons, bicycles and motorbikes

How and what objects are detected?

- Used **opencv's (image processing python package)** pre-trained DeepNeuralNetwork(DNN) object detection model **(MobileNet SSD ver3)** to detect objects in images
  - Pre-trained to detect 80 different types of objects such as person, car from the popular computer vision dataset MS COCO dataset
  - Confidence threshold set at 50%, only objects detected with at least 50% confidence level will be recorded
- Manual checking is done to filter out objects that are wrongly detected by the model and are not present in any of the images (E.g bird, boat, laptop)

Outcome

- **149 images with at least 1 object detected (out of 220)**
- **8 Types of Objects detected in ALL 149 images**

OBJECT DETECTION

Correlation analysis result
where the 8 strongly correlated objects are ordered in descending order (from left to right)

P-value <= 0.05 : effect of the color in the images on the image ratings given is **statistically significant** at 5% significance level

Beautiful

Objects detected	truck	person	train	bicycle	motorbike	bus	traffic light	car
	-0.2566	-0.1390	-0.1322	-0.1227	-0.0636	-0.0427	-0.0074	-0.0006
P-value	0.0001	0.0394	0.0501	0.0692	0.3479	0.5285	0.9132	0.9922

Safe

Objects detected	truck	traffic light	car	bus	motorbike	person	bicycle	train
	-0.2670	-0.1697	-0.1317	-0.1185	-0.0798	0.0340	0.0310	0.0183
P-value	0.00006	0.61563	0.05104	0.07944	0.23830	0.01172	0.64790	0.78668

Welcome

Objects detected	truck	traffic light	train	car	bicycle	person	bus	motorbike
	-0.26299	-0.1235	-0.0976	-0.0653	-0.0398	0.0383	-0.0324	-0.0080
P-value	0.00008	0.06751	0.14922	0.33528	0.55726	0.57245	0.63234	0.90644

Insights

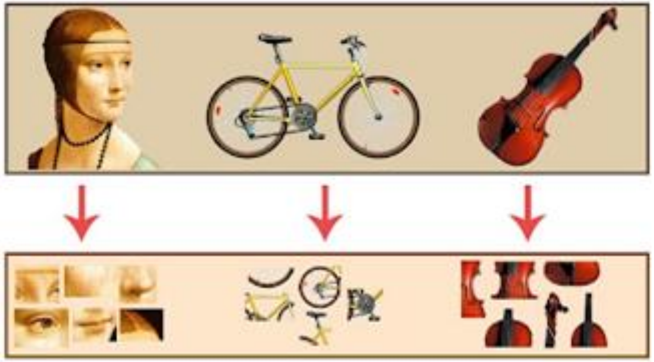
- **Presence of Trucks in images leads to lower Beautiful, Safe and Welcome ratings**
- **Presence of Persons in images leads to higher Beautiful & Safe ratings**

IMAGE ANALYSIS

BAG OF VISUAL WORDS

Based on overall median ratings on each of the 220 images

BAG OF VISUAL WORDS



To identify the images features that are crucial in rating images as **beautiful**, **safe** and **welcome**

What and how to extract image features?

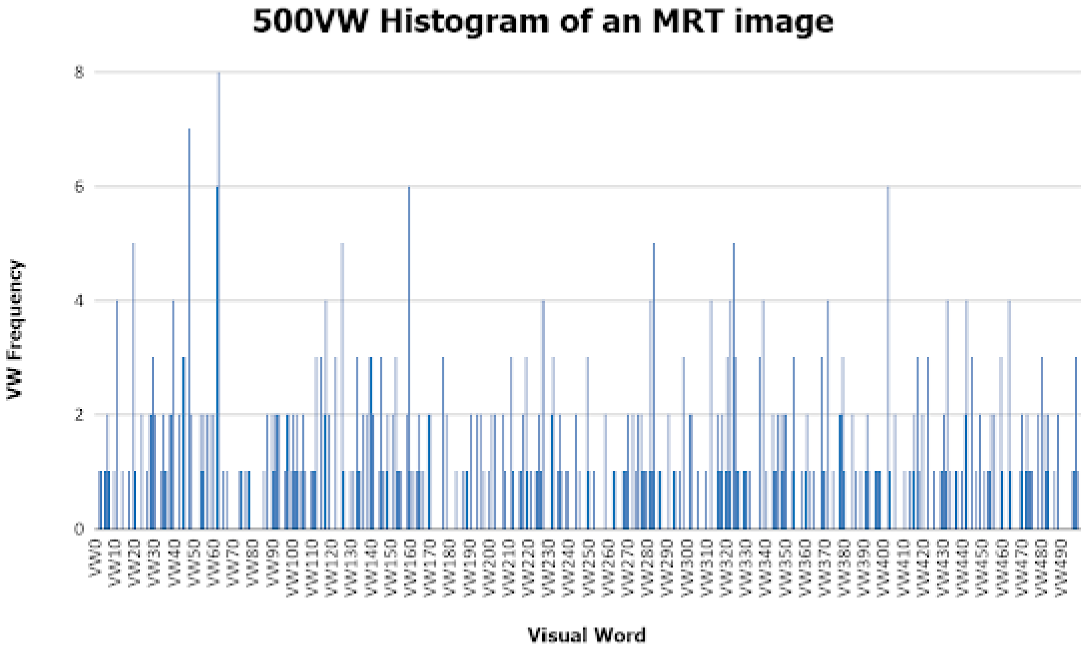
- Use **skimage's Oriented FAST** and **Rotated BRIEF(ORB)** feature detector, robust and fast in extracting key features from all 220 images
- **K-means Clustering** is subsequently used to group the image features into 500 clusters (referenced from London paper) based on inherent similarity. Within each group, image features are highly *similar*. Across each group, image features would be highly *different*
- **500 "visual words"** (VW) (image feature in each of the 500 cluster centers) that are most representative from all 220 images would be selected

Outcome
Obtained 500 representative visual words from 220 images

BAG OF VISUAL WORDS

Compute the 500 VW histogram

- Compute the **frequencies of each VW** in each image for all 220 images



Perform **correlation analysis** (Pearson's correlation) to select the visual words that have a strong linear relationship with image perception ratings for each of the 3 image metrics (**Beautiful**, **Safe**, **Welcome**)

- Strong correlation value set at **>=0.10** or **<-=0.10**
  (referenced from the London paper)

Outcome

- **Obtained counts for 500 Visual Words in each of the 220 images**
- **Obtained 115, 90 and 94 strongly correlated Visual Words with Beautiful, Safe and Welcome respectively**

BAG OF VISUAL WORDS

Blue dots signify the locations of the strongly correlated visual words that can be found in the images

Insights

- Grass, Blue Skies →

  correlated with Most Beautiful
- MRT tracks, Barricades, Trucks , Bicycles →

  correlated with Least Beautiful

Most **beautiful** MRT stations and its surroundings

CITY HALL MRT STATION

RAFFLES PLACE MRT STATION

Least **beautiful** MRT stations and its surroundings

ANG MO KIO MRT STATION

SERANGOON MRT STATION

BAG OF VISUAL WORDS

Blue dots signify the locations of the strongly correlated visual words that can be found in the images

Insights

- Trees, Shelters →

  correlated with Most Safe
- Vans, Trucks, Lorries→

  correlated with Least Safe

Most **safe** MRT stations and its surroundings

CHINESE GARDEN MRT STATION

YIO CHU KANG MRT STATION

Least **safe** MRT stations and its surroundings

PUNGGOL MRT STATION

BISHAN MRT STATION

BAG OF VISUAL WORDS

Blue dots signify the locations of the strongly correlated visual words that can be found in the images

Most **welcome** MRT stations and its surroundings

TIONG BAHRU MRT STATION

UPPER CHANGI MRT STATION

Least **welcome** MRT stations and its surroundings

SERANGOON MRT STATION

BISHAN MRT STATION

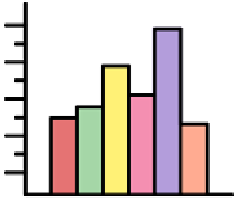
Insights

- Wide Roads, Blue Skies, Shelter, Trees and persons→ correlated with Most Welcome
- Bus Stops, White Barricades, and Trucks → correlated with Least Welcome

BAG OF VISUAL WORDS

Build a binary classification model that can predict whether an image is beautiful, safe and welcome, based on the strongly correlated visual words histogram

- **Decision rules** for classification of prediction
  - **Recap:** image ratings ranges from 1(Strongly disagree) to 5(Strong agree)
  - If **image rating <= 3**, classify image as **NOT** beautiful/safe/welcome (“No”)
  - If **image rating >3**, classify image as beautiful/safe/welcome (“Yes”)
- Choice of **classification of Machine Learning model**
  - **Support Vector Machine** (SVM)



Strongly correlated VW histogram for this image

Trained classification Model

Predicted Image rating = “Yes”

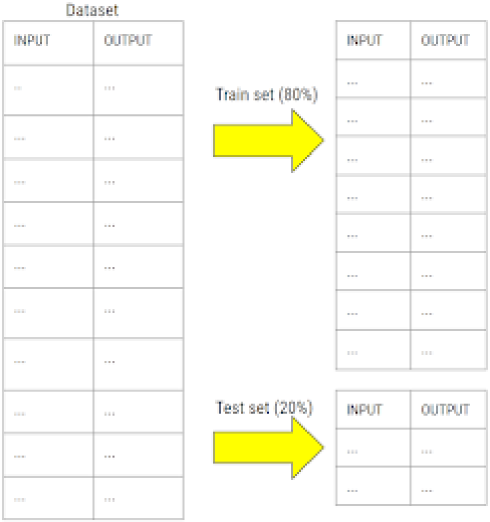
Outcome

Transform output variable in dataset (image ratings) from Numerical to Categorical data type

BAG OF VISUAL WORDS

Build a binary classification model that can predict whether an image is beautiful/safe/welcome, based on the strongly correlated visual words histogram

Image metrics	Beautiful	Safe	Welcome
Input variables: Strongly correlated VW histogram	115 VW histogram	90 VW histogram	94 VW histogram
Output variable; Image ratings (“Yes”/No”)	55% “No” , 45% “Yes”	63% “No” ,37% “Yes”	56% “Yes”, 44% “No”



Training and testing the performance of classification model

- Dataset is split into 5 different pairs of 80% training and 20% testing sets in a manner where the class proportion of the output variable in the original dataset is maintained

Insights

- **Dataset is quite well-balanced**

  (proportion of classes of the output variable is relatively equal)

BAG OF VISUAL WORDS

Accuracy =
the “correctness” of all (YES, NO) predictions

Precision =
For all the predictions made, how many are actually correct?

Recall =
For all the actual results, how many did the the model manage to predict

F1 score =
weighted average of precision and recall

Evaluation of the performance of the classification model based on the mean scores from 5 pairs of training and test sets

Image metrics	Accuracy score	Precision score	Recall score	F1 score
Beautiful	0.64+- 0.076	0.60+-0.099	0.64+-0.183	0.61+-0.099
Safe	0.63+-0.055	0.71+-0.029	0.69+-0.104	0.70+-0.061
Welcome	0.64+-0.025	0.58+-0.023	0.64+-0.038	0.61+-0.026

Outcome

- Classification model which can be used determine which MRT stations need improvement in the aspects of Beautiful, Safe, Welcome

Insights

- The classification model is relatively good in predicting of whether an image is Beautiful / Safe / Welcome
- There is greater consistency in how people perceive image as Safe, thus the classification model is able to learn the patterns easily and make more accurate predictions for Safe

Summary of Insights

From descriptive statistics, colours, object detection and visual words

SUMMARY OF INSIGHTS

Expected Outcome

To discover the visual elements that defines the qualities of "Beautiful", "Safe" and "Welcome in the eyes of the Singapore public

	Beautiful	Safe	Welcome
Descriptive Stats	• Beautiful images tend to contain greenery • Unbeautiful images tend to contain trucks and bicycles	• Beautiful images tend to contain greenery • Unbeautiful images tend to contain trucks and bicycles	• Welcoming images tend to contain greenery and houses • Unwelcoming images tend to contain dull and greyish colour tones and trucks
Colours	• Greater average greenness in images lead to higher beautiful image ratings • Greater average redness in images lead to lower beautiful image ratings • More blue-magenta color in images lead to higher beautiful image ratings	• More light pink color in images lead to lower safe image ratings • More dark green color images lead to higher safe image ratings	• Greater average greenness in images lead to higher welcome image ratings • Greater light red color in images lead to higher welcome image ratings
Object Detection	Presence of Trucks in images leads to lower Beautiful, Safe and Welcome ratings		
	Presence of Persons in images leads to higher Beautiful ratings		Presence of Persons in images leads to higher Safe ratings
Visual Words	• Beautiful images tend to contain grass and blue skies • Unbeautiful images tend to contain • MRT tracks, Barricades, Trucks and Bicycles	• Safe images tend to contain trees and shelters • Unsafe images tend to contain vans, trucks, and lorries	• Welcoming images tend to contain wide roads, blue skies, shelter, trees and persons • Unwelcoming images tend to contain bus stops, white barricades, and trucks

Project Schedule

Status Update

PROJECT SCHEDULE

LEGEND

Achievements ✓ Done ••• Ongoing ⚠ Delayed

PHASE 1 | Defining Project Methodology

TASK 1 - DISCUSS ABOUT THE PROJECT METHODOLOGY INDEPTH	✓
TASK 2 - DECIDE ON SURVEY PLATFORM AND APPROACH	✓
TASK 3 - SELF LEARN ON EXTRACTING IMAGES AND IMAGE ANALYSIS	⚠
BI-WEEKLY MEETING WITH PROJECT SPONSOR	✓

PHASE 3 | Analysing Data Insights

TASK 8 - PREPARE CODES FOR IMAGE ANALYSIS	⚠
BI-WEEKLY MEETING WITH PROJECT SPONSOR	✓
TASK 9- DATA PROCESSING AND CLEANING OF ANNOTATED IMAGES	⚠
MILESTONE 1 - MID-TERM PRESENTATION	Achievements
TASK 10 - ANALYSE THE ANNOTATED IMAGES	⚠
BI-WEEKLY MEETING WITH PROJECT SPONSOR	✓
TASK 11 - REPRESENT DATA INSIGHTS IN VISUALISATIONS	✓

PHASE 2 | Preparing for Data Collection

TASK 4 - EXTRACTING IMAGES FROM GOOGLESTREETVIEW API	✓
TASK 5 - SET UP SURVEY PLATFORM	✓
TASK 6 - DISTRIBUTE SURVEY & WAIT FOR RESPONSES	⚠
BI-WEEKLY MEETING WITH PROJECT SPONSOR	✓
TASK 7- PREPARE FOR MID-TERM PRESENTATION	✓

PHASE 4 | Preparing for Data Collection

BI-WEEKLY MEETING WITH PROJECT SPONSOR	✓
TASK 12 - PREPARE FOR FINAL PRESENTATION	✓
TASK 13 - PREPARE FOR FINAL REPORT	•••
MILESTONE 2 - FINAL PRESENTATION	Achievements
MILESTONE 3 - FINAL REPORT	•••

IMPACT TO SOCIETY

PROJECT'S IMPACT TO SOCIETY

11 SUSTAINABLE CITIES AND COMMUNITIES

- Informs **public policy decision-making** as mentioned by Idrovo and Duarte (2015)

  E.g. beneficial to **urban planners**

  - (Quercia et al., 2014) demonstrated the viability of the recommendations gleaned the analysis of perceptions of the urban environment with **architects**
- Promotes the virtue of **co-creation** and **civic participation** in national issues (Ministry of Culture, Community and Youth, 2019)
  - Helps to improve **public trust** in the government (Chiang & Soon, 2019)
  - Boost **citizens' confidence** in the value of their contributions (Soon & Sim, 2021)

Together, our project will help to promote and contributes towards Singapore's strong commitment in achieving the United Nations Sustainable Development Goal (SDG) (**"Goal 11: Makes cities inclusive"**)

IMPACT TO SPONSOR

PROJECT’S IMPACT TO SPONSOR

Feasibility of Our Project Methodology

From collection of images, crowdsourcing perceptions to image analysis methods , is it meaningful to carry out in a larger-scale to the Singapore population?

Findings from Survey Insights

From our survey insights, is there any interesting findings that is worthy to extend similar research study on other aspects of Singapore urban landscapes

We hope that our project will help our sponsor to better conduct similar research studies to the Singapore population

PROJECT CHALLENGES

LIST OF CHALLENGES

Challenge	Response
Steep Learning Curve in image analysis techniques	Read up other relevant research papers and online sources Consulted project sponsor for guidance
Unexpected delays due to administrative matters relating to IRB approval on survey	Sent out pilot survey Faster turnaround time when liaising with project sponsor regarding IRB approval matters
Time-consuming collection of primary data (survey)	Incentivise the participants by providing reimbursement of $5 grab transport vouchers to the first 50 participants

FUTURE WORK

FUTURE WORK

Collect images that are more representative of Singapore

Use grid-based geographic sampling method to collect images that are more representative of Singapore due to the limitations of Google Street View API

Increase the volume and quality of survey data

Increase the number and demographic representativeness of survey responses from the Singapore Public to improve validity and correctness of analysis results

Increase relevancy of Object Detection model

Improve object detection model to detect greater variety of objects (e.g. trees and buildings) such that it is more relevant to our analysis of images

“ *Thank you, Q&A*

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