468 0

SHOP

EQUIPMENT

CHAMPIONS

SKINS

BIG DATA MANAGEMENT PROJECT

Amber Yeo (222809U),
Javerine Tan (220429P),
Jess Lim (211031L)

START

BACKGROUND INFORMATION

- Rising popularity of online multiplayer games
- Top e-games: League of Legends, Dota 2 and Valorant
- Professional leagues and large-scale tournaments were established
- Attracted large investments and sponsors, increasing its outreach
- Gap in understanding match behaviour, demographic trends and community sentiments
- More analysis into them can help improve the success of the e-sports industry

368 2

GROUP PROBLEM STATEMENT

- Issues in player retention and satisfaction
- Initial negative experiences for Newcomers
- Difficulty in keeping up with the growing number of game options for Seasoned Players

PROPOSED SOLUTION

To provide a detailed analysis of game play, demographic trends, and community feedback, focusing on 3 popular e-sports games: League of Legends (LOL), Dota 2, and Valorant.

Ultimately helping stakeholders improve game enjoyment, informed of current trends, and community involvement.

368 2

SHOP

EQUIPMENT

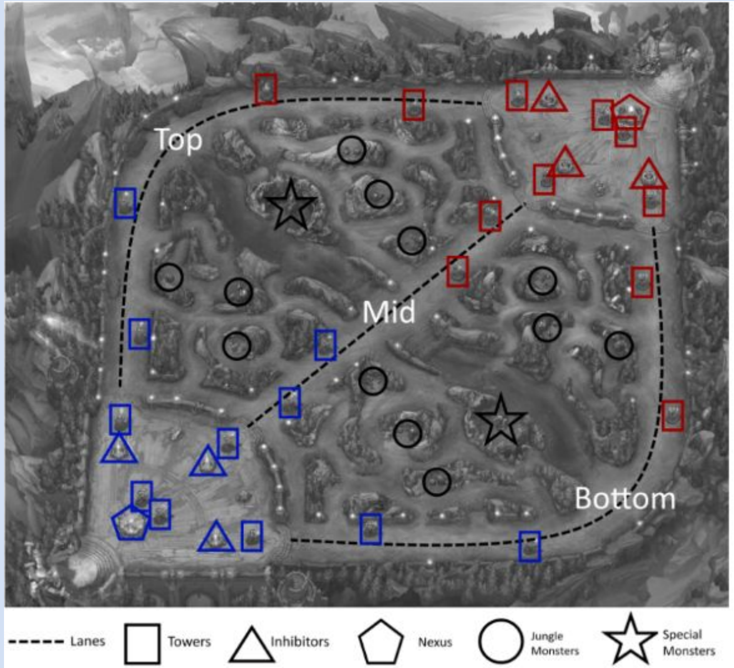
CHAMPIONS

SKINS

01 Match Performance

Match attributes and statistics in League of Legends affects game outcomes

Game Play



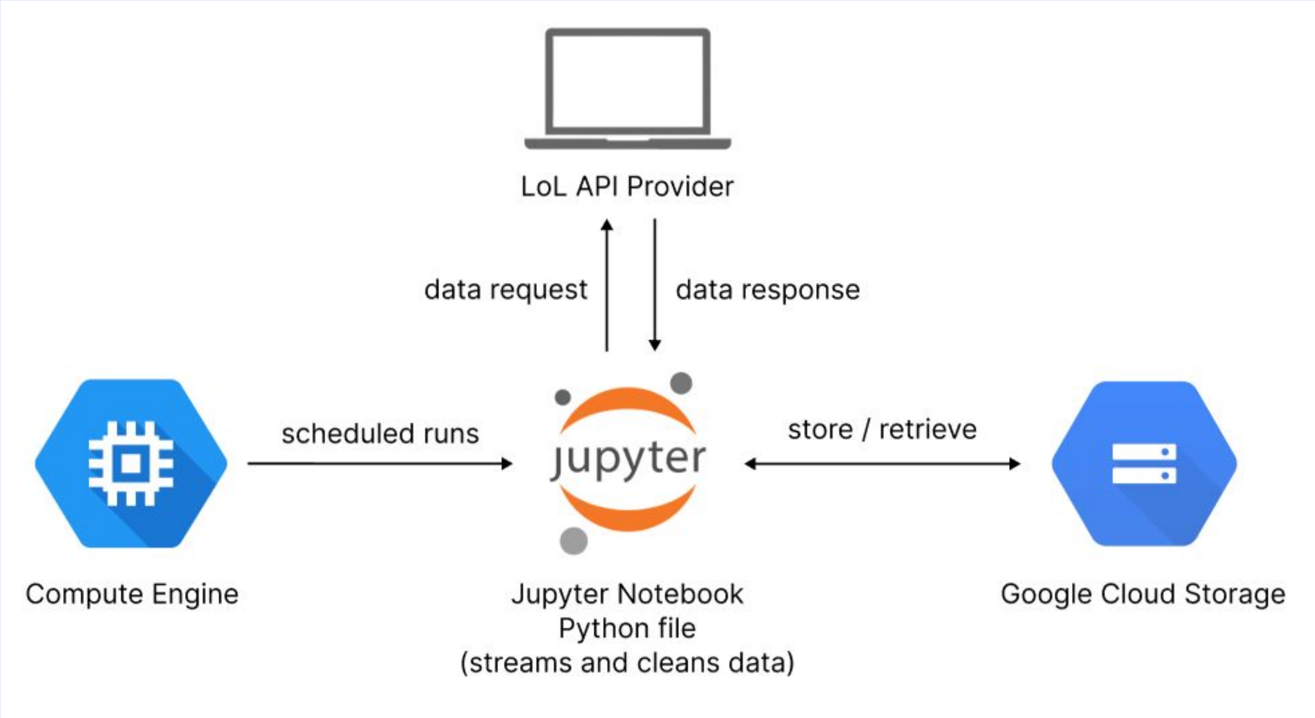
4 lanes: Top (fighter) , Mid (mage), Bottom (marksman, support, tank) and Jungle (goes around killing monsters; assassin)

How to win: The first team to destroy the opponent's Nexus

Earn gold: Kill monsters, opponent minions, champions or towers

Special Monsters: Gives team that kills it buff for a limited time

Data Streaming Pipeline



Features

Match statistics :

- Game duration
- Game outcome
- Player position
- Champion chosen
- Champion role
- Kills
- Death
- Assists
- Gold earned
- Item stats
- Perks stats
- etc

Player statistics:

- ID
- League points
- Wins
- Losses
- Platform
- Region
- Inactive

Predicting Game Outcome

<u>Parameters</u>

Using PyCaret Classification

- Target = player_win
- Features = match statistics (54 columns)
  - eg Kills-Deaths-Assists, total kills, game duration, dragon kills
- Ignore features
  - items and perks information (reduce complexity)
  - player lane, position (all matches have a balanced number so it does not affect win rates)
- Normalise = True
- Remove outliers = True

Predicting Game Outcome

Compare models

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
catboost	CatBoost Classifier	0.9709	0.9967	0.9748	0.9672	0.9710	0.9417	0.9418	36.0180
lightgbm	Light Gradient Boosting Machine	0.9683	0.9964	0.9723	0.9647	0.9685	0.9366	0.9366	6.7090
gbc	Gradient Boosting Classifier	0.9627	0.9946	0.9647	0.9610	0.9628	0.9255	0.9255	26.1260
rf	Random Forest Classifier	0.9605	0.9936	0.9697	0.9524	0.9609	0.9211	0.9213	9.9630
lr	Logistic Regression	0.9565	0.9918	0.9594	0.9540	0.9567	0.9131	0.9131	1.0400
et	Extra Trees Classifier	0.9559	0.9927	0.9663	0.9466	0.9564	0.9117	0.9119	5.7330
ada	Ada Boost Classifier	0.9547	0.9923	0.9516	0.9577	0.9546	0.9094	0.9095	5.5950
svm	SVM - Linear Kernel	0.9544	0.9904	0.9560	0.9531	0.9545	0.9088	0.9089	0.8540
ridge	Ridge Classifier	0.9527	0.9905	0.9517	0.9537	0.9527	0.9054	0.9055	0.7900
lda	Linear Discriminant Analysis	0.9527	0.9905	0.9517	0.9537	0.9527	0.9054	0.9054	1.2130
dt	Decision Tree Classifier	0.9438	0.9438	0.9421	0.9454	0.9437	0.8876	0.8876	1.6370
knn	K Neighbors Classifier	0.9308	0.9727	0.9332	0.9289	0.9311	0.8617	0.8617	6.2370
nb	Naive Bayes	0.8437	0.9109	0.8557	0.8360	0.8457	0.6875	0.6877	0.7140
qda	Quadratic Discriminant Analysis	0.5638	0.6246	0.4183	0.6674	0.4466	0.1277	0.1581	1.4240
dummy	Dummy Classifier	0.4996	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0690

Best is catboost BUT the time taken is significantly higher than the second best

Therefore will be using lightgbm model instead

Predicting Game Outcome

Tuning Best Model Hyper-parameters

	Best Hyper-parameters returned	Mean Accuracy
Default	min_child_samples=20, min_split_gain=0.0, n_estimators=100, num_leaves=31, random_state=123, reg_alpha=0.0, reg_lambda=0.0, learning_rate=0.1	0.9683
Tuned 1 (10 iterations)	min_child_samples=66, min_split_gain=0.4, n_estimators=90, num_leaves=90, random_state=123, reg_alpha=0.0005, reg_lambda=0.1, learning_rate=0.1, bagging_fraction=0.6, bagging_freq=6, feature_fraction=0.5	0.9685
Tuned 2 (50 iterations)	min_child_samples=26, min_split_gain=0.6, n_estimators=160, num_leaves=200, random_state=123, reg_alpha=0.2, reg_lambda=0.005, learning_rate=0.05, bagging_fraction=0.9, bagging_freq=0, feature_fraction=0.6,	0.9707

Best Team Champion Combination

Parameters

Using Association Rule mining, FP-growth

- Filter to only contain winning team composition
- One-Hot encoding of champion used
- Each row is a winning team's team composition

Find rules that shows the common champion combinations of winning team

Calculate win rates using mined rules composition found
(only keeps combination picks if win rates > 55%)

Best Team Champion Combination

Tuning Best Model Hyper-parameters

- Support is how frequently the items in a rule appear together in the dataset
- Confidence is the likelihood that the champion recommended is picked when another champion was already picked in your team

	Hyper-parameters	Rules Found
Default	fp-growth: min support = 0.5 (at least 8236 matches) association rules: metric="confidence", min_threshold=0.5	0
Tuned 1	fp-growth: min support = 0.0012 (at least 20 matches) association rules: metric="confidence", min_threshold=0.05	2813
Tuned 2	fp-growth: min support = 0.0012 (at least 20 matches) association rules: metric="support", min_threshold=0.001 (at least 33 matches)	6368

Best Champion Counter Picks

Parameters

Using Association Rule mining, FP-growth

- Transform into 2-dimensional array,
  - red_team_champs, blue_team_champs
- Flatten into 1-dimension
- One hot encode champion names

Find rules that shows the common counter pick(s) given the opponent pick(s) of all matches

Win rates is calculated to find which counters give the best win rates (only keeps counter picks if win rates > 55%)

Best Champion Counter Picks

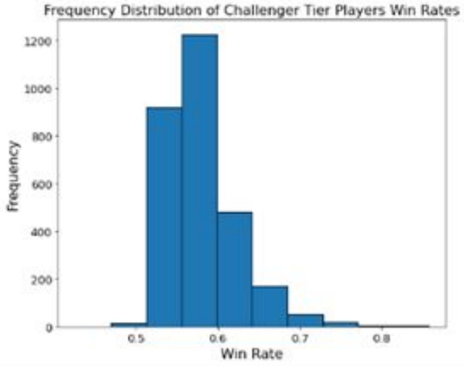
Tuning Best Model Hyper-parameters

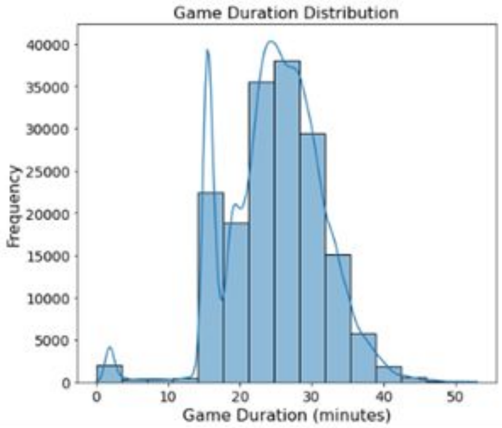
	Hyper-parameters	Rules Found
Tuned 1	fp-growth: min support = 0.01 (at least 164 matches) association rules: metric="support", min_threshold=0.01 (at least 159 matches)	202
Tuned 2	fp-growth: min support = 0.005 (at least 82 matches) association rules: metric="support", min_threshold=0.001 (at least 80 matches)	894
Tuned 3	fp-growth: min support = 0.001 (at least 16 matches) association rules: metric="support", min_threshold=0.001 (at least 16 matches)	19398
Tuned 4	fp-growth: min support = 0.003 (at least 49 matches) association rules: metric="support", min_threshold=0.001 (at least 48 matches)	2494

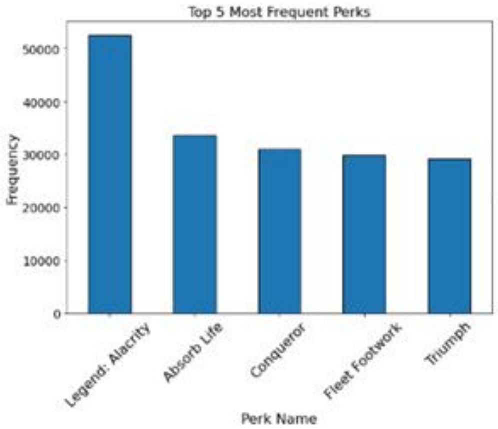
DataBricks Dashboard

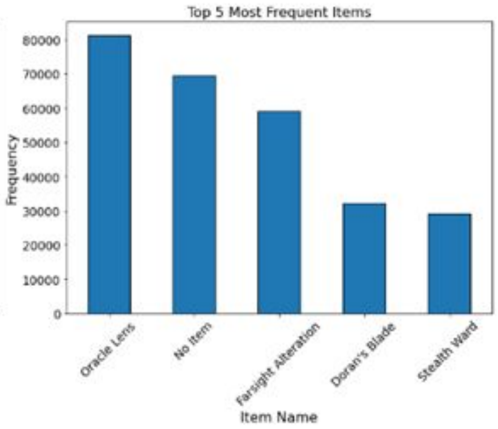
Data Statistics

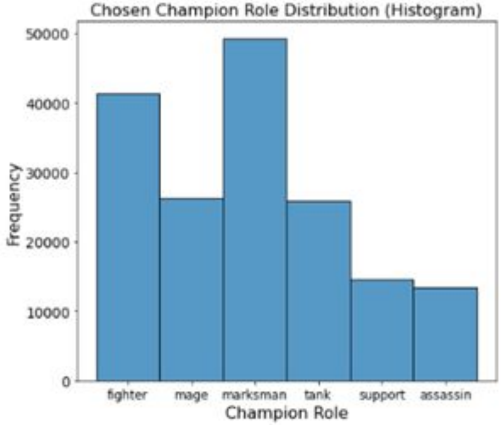
Player Data



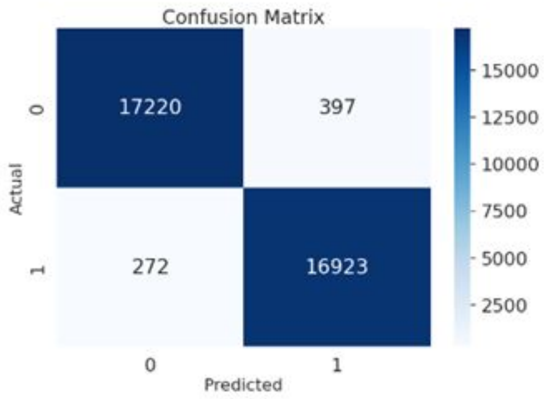






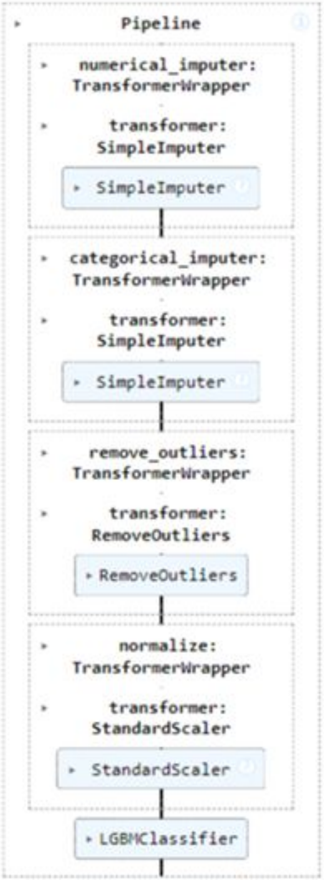


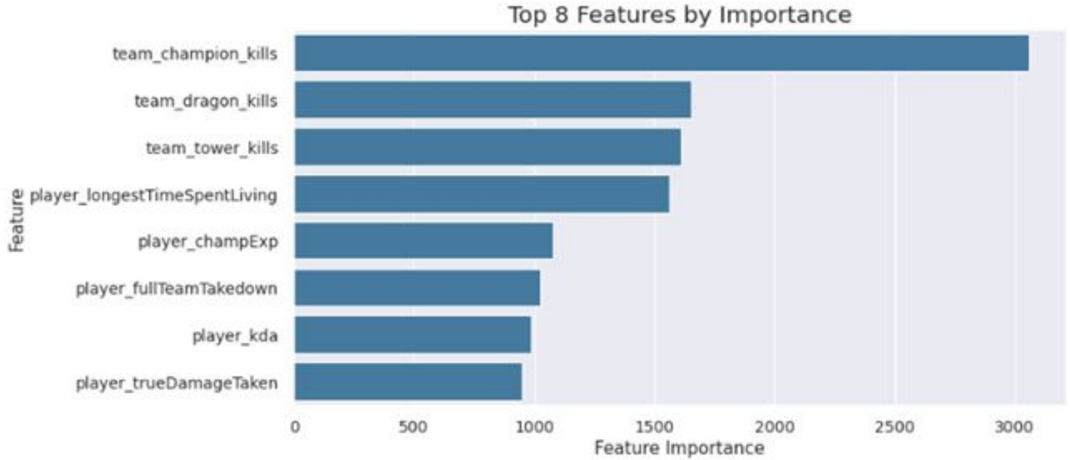
Game Outcome Performance



Prediction Report

	precision	recall	f1-score	support
False	0.984	0.977	0.981	17617.0
True	0.977	0.984	0.981	17195.0
accuracy	0.981	0.981	0.981	0.981
macro avg	0.981	0.981	0.981	34812.0
weighted avg	0.981	0.981	0.981	34812.0





Champion Selection

Best Team Composition

	Ally Chosen pick	Best Next Ally Pick	1.2 win_rate	Count
1	('Bard',)	('DrMundo',)	86.956522	23
2	('Ryze',)	('Ashe',)	86.363636	22
3	('Belveth',)	('Poppy',)	84	25
4	('Alistar', 'Lillia')	('Kaisa',)	77.142857	35
5	('Ezreal', 'Kennen')	('Tristana',)	76	25

Top Played Champions by Role

	Role	Champion	1.2 Usage Rate %
1	assassin	Nidalee	16.37
2	fighter	LeeSin	15.6
3	mage	Brand	12.64
4	marksman	Kaisa	35.19
5	support	Rakan	10.66
6	tank	Leona	21.34

Top Champion Counters

	Opponent Chosen pick	Ally Pick	1.2 win_rate	count
1	('Kaisa', 'Zeri')	('Corki',)	76.923077	51
2	('Kalista',)	('Ezreal',)	71.666667	60
3	('Kaisa',)	('Ezreal', 'Rell')	71.428571	69
4	('Azir',)	('Viego',)	71.428571	48
5	('Camille',)	('Jax',)	69.230769	91

Top Banned Champions

	Role	Champion	1.2 Ban Rate %
1	marksman	Draven	38.69
2	assassin	LeBlanc	35.09
3	support	Pyke	35
4	mage	Karthus	33.23
5	assassin	Nidalee	32.67

Match Scenario : Using Kaisa (Marksman)

Best Team Composition

	Parameter	Value
1	Ally Chosen pick	('Alistar', 'Lillia')
2	Best Next Ally Pick	('Kaisa',)
3	win_count	27
4	win_rate (%)	77.14285714285715

Win Outcome Prediction

	prediction_label	prediction_score
1	1	0.9935

Feature Values

	Feature	Value
1	match_gameDuration	1571.0
2	team_champion_kills	20.0
3	team_dragon_kills	2.0
4	team_tower_kills	11.0
5	player_longestTimeSpentLiving	826.0
6	player_champExp	1263.0
7	player_fullTeamTakedown	1.0
8	player_kda	4.0
9	player_trueDamageTaken	897.0
10	player_totalDamageTaken	20165.0

However,

	Parameter	Value
1	Ally Pick	('Kaisa',)
2	Opponent Chosen pick	('Ezreal', 'Rell')
3	win_rate	71.42857143
4	count	69

Recommendations

To increase your win probability, you should :

Optimise champion chosen based on ally pick (best champion synergy) or opponent pick (best champion counters).

You can should also take note of your champion experience, Kills-Deaths-Assists, total champion kills, damage taken, tower and dragon kills, and stay alive longer

854 10

SHOP

EQUIPMENT

CHAMPIONS

SKINS

THANKS!

END