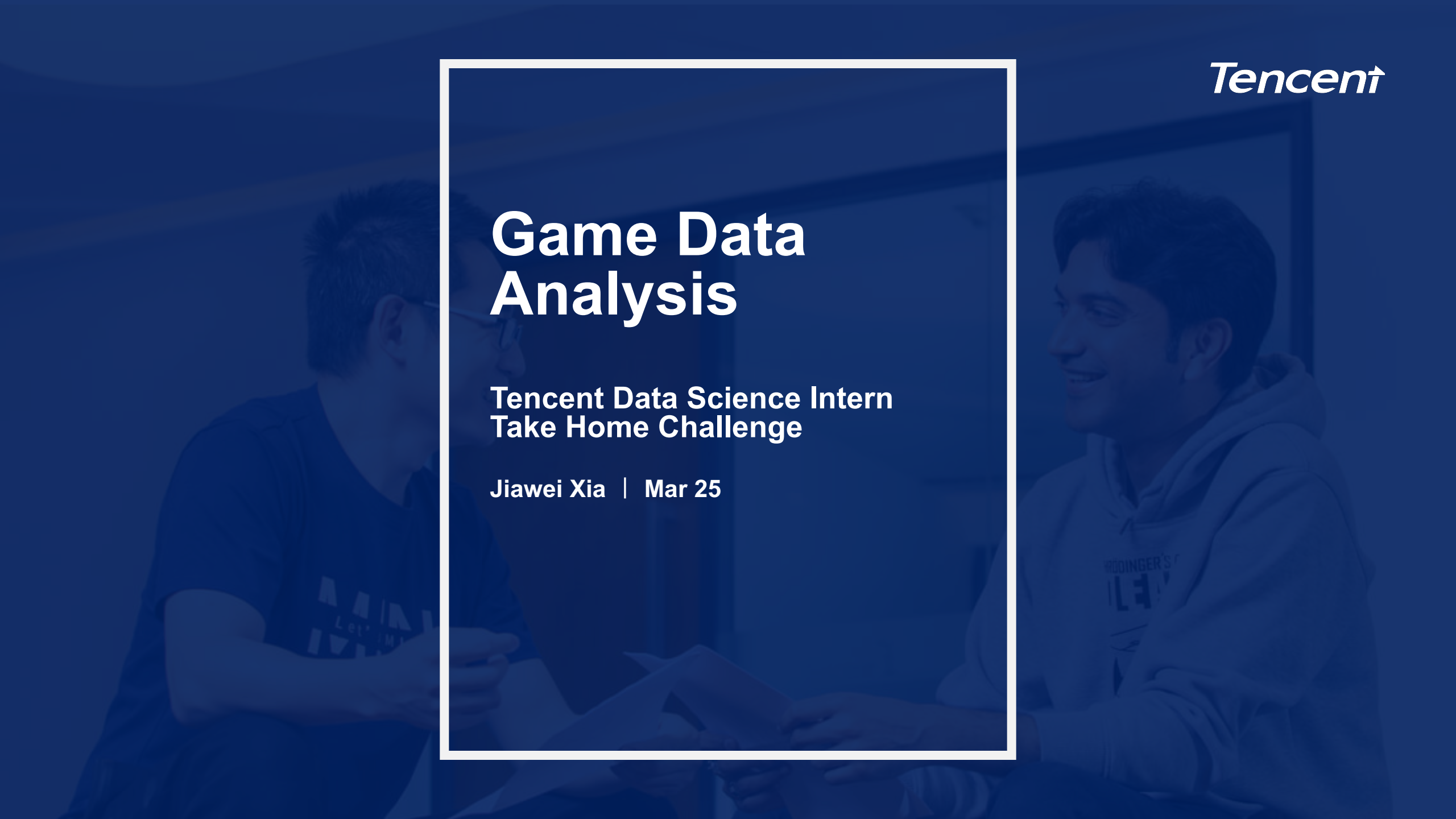


Game Data Analysis

Tencent Data Science Intern Take Home Challenge

Jiawei Xia | Mar 25

Content

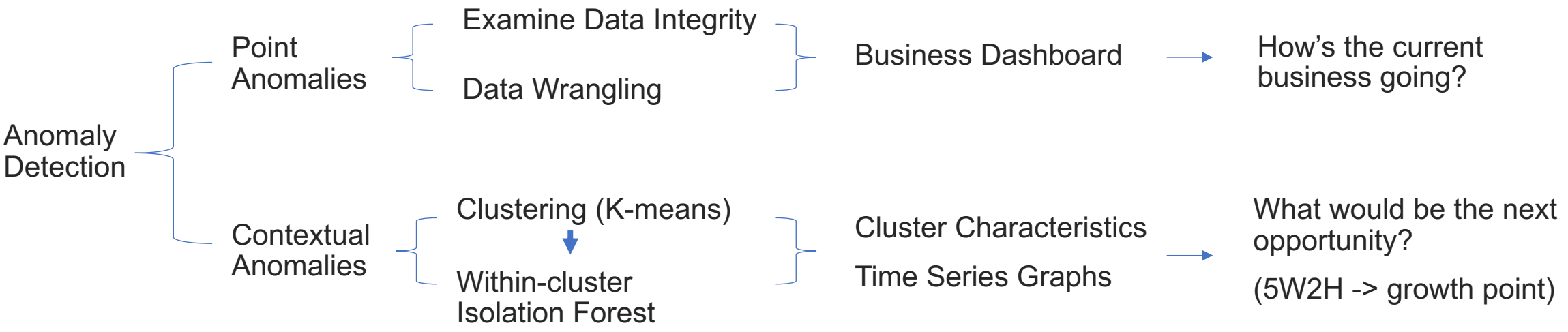
Tencent

01 Anomaly Detection

02 Data Science (Clustering/Prediction)

03 Visualization/ Time Series

04 Questions Answered



Point Anomalies

Examine Data Integrity ✔

Data Wrangling

Data Frame

- Head sample data
- Shape (748264 x 14)
- Data types
- Missing values (0)

Actions:

- Transform str object into datetime for “Date”

Columns

- Date range (from 2018-03-15 to 2020-03-09)
- Countries (239)
- Platforms (3)
- Key stats (min, max, etc)
- Duplicated columns (1)

Actions:

- Remove anomalies disobeying business rules
- Drop the second “Date”

Rows

- Duplicated rows (~50%)
- Conflicting rows (in country ‘Dominica’)
- Inconsistent country format

Actions:

- Drop repeated rows
- Drop conflicting rows
- Translate zh-cn to en

Pairwise

- Diagonal: concentrated data
- Line shape: possible linear relationship
- L shape & U shape: 2 possible clusters
- E shape: 3 possible clusters

Actions:

- Assumption for clustering k=2 or 3
- Linear correlation

Point Anomalies

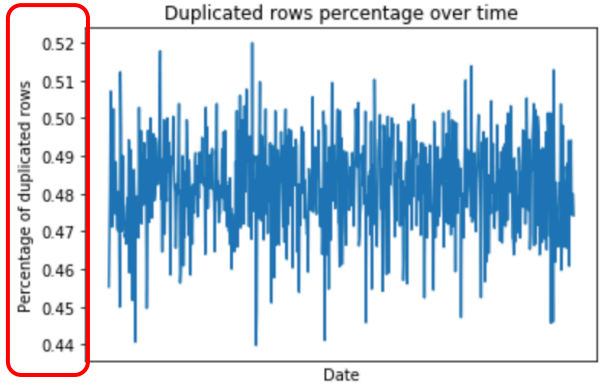
Examine Data Integrity

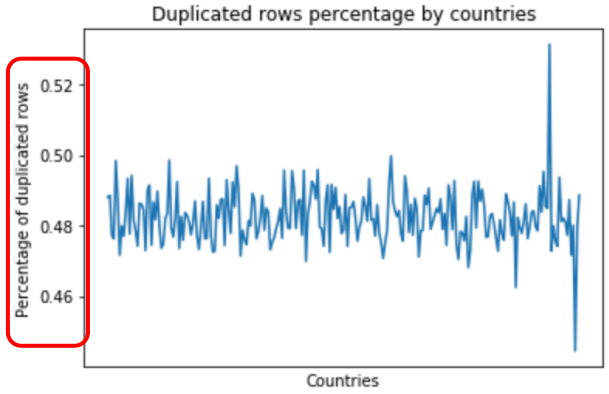
Data Wrangling

Date	object
Date.1	object
Platform	object
Country	object
TRU	float64
DAU	float64
Items	float64
Trans	float64
Items Per Trans	float64
Items per DAU	float64
Conversion	float64
Cash Flow	float64
Return Customer	float64
Time Spend Per Day(seconds)	float64

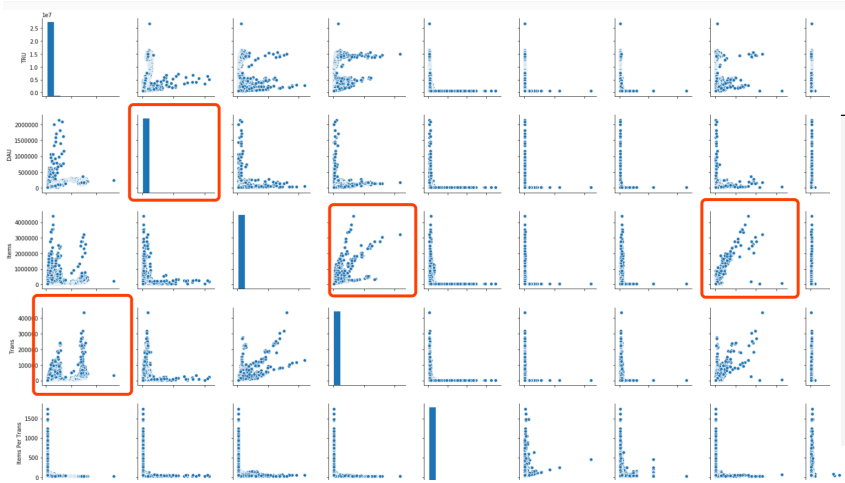
dtype: object

Iran(伊朗)	3441
Australia(澳大利亚)	3434
圣卢西亚	3366
Israel(以色列)	3365
Iraq(伊拉克)	3363
...	
厄立特里亚	529
托克劳	496
圣巴泰勒米	239
unknown(未知)	31
蒙塞拉特岛	18





	TRU	DAU	Items	Trans	Items Per Trans	Items per DAU	Conversion	Cash Flow	Return Customer	Time Spend Per Day(seconds)
count	7.482640e+05	7.482640e+05	7.482640e+05	748264.00000	748264.000000	748264.000000	748264.000000	748264.000000	748264.000000	748264.000000
mean	7.399568e+05	1.816949e+04	5.089120e+04	3958.49364	31.569433	1.414330	2.902036	5093.453512	39.795054	122.605716
std	6.776595e+05	1.801799e+04	4.610241e+04	3655.62504	23.629177	1.208879	2.591666	4712.790645	24.796009	43.331318
min	6.286478e+05	1.529217e+04	4.342911e+04	3428.09000	17.580000	1.300000	2.300000	4527.010000	12.210000	-9.990000
25%	6.288102e+05	1.529677e+04	4.342911e+04	3428.09000	17.580000	1.300000	2.300000	4527.010000	28.660000	98.950000
50%	6.314452e+05	1.537393e+04	4.352124e+04	3433.85000	28.090000	1.320000	2.560000	4532.770000	39.430000	118.180000
75%	6.574735e+05	1.617663e+04	4.466021e+04	3522.53000	36.080000	1.390000	3.000000	4611.080000	48.920000	139.370000
max	2.677675e+07	2.141935e+06	4.387412e+06	434846.58000	1744.870000	444.240000	232.630000	819825.280000	3912.090000	1390.060000



Country	Date	Platform	TRU	DAU	Items
	2018-03-16	4	4	4	4
	2018-03-19	5	5	5	5
	2018-03-20	5	5	5	5
	2018-03-22	5	5	5	5
	2018-03-23	5	5	5	5
Dominica	...	...	...	...	...
	2020-03-05	6	6	6	6

Point Anomalies

Examine Data Integrity ✔

Data Wrangling ✔

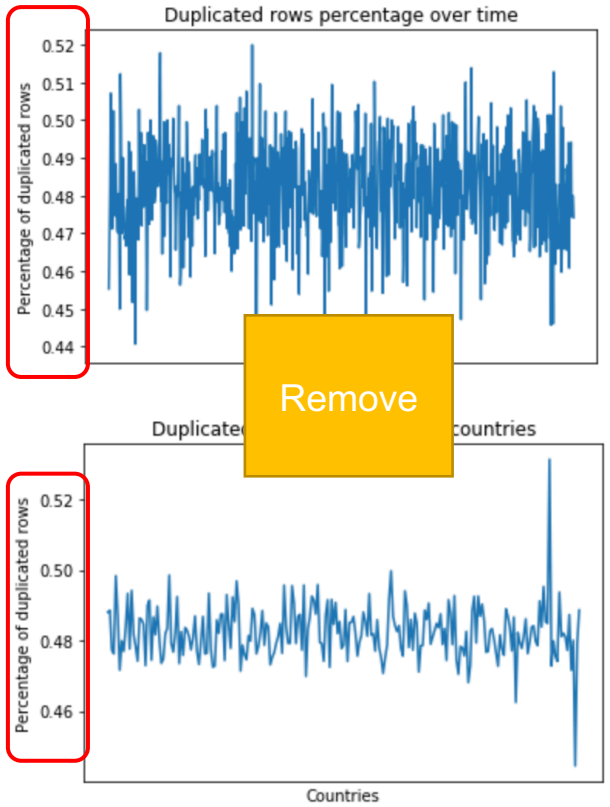
```
Date                          object
Date.1                        object
Platform                      object
Country                       object
TRU                          float64
DAU                          float64
Items                        float64
Trans                        float64
Items Per Trans              float64
Items per DAU                float64
Conversion                   float64
Cash Flow                    float64
Return Customer              float64
Time Spend Per Day(seconds)  float64
dtype: object
```

Drop

Transform

```
Iran(伊朗)                    3441
Australia(澳大利亚)           3434
圣卢西亚                      3366
Israel(以色列
Iraq(伊拉克)
                              ...
厄立特里亚                     529
托克劳                         496
圣巴泰勒米                     239
unknown(未知)                   31
蒙塞拉特岛                      18
```

Translate



	TRU	DAU	Items	Trans	Items Per Trans	Items per DAU	Conversion	Cash Flow	Return Customer	Time Spend Per Day(seconds)
count	7.482640e+05	7.482640e+05	7.482640e+05	748264.00000	748264.000000	748264.000000	748264.000000	748264.000000	748264.000000	748264.000000
mean	7.399568e+05	1.816949e+04	5.089120e+04	3958.49364	31.569433	1.414330	2.902036	5093.453512	39.795054	122.605716
std	6.776595e+05	1.801799e+04	4.610241e+04	3655.62504	23.629177	1.208879	2.591666	4712.790645	24.796009	43.331318
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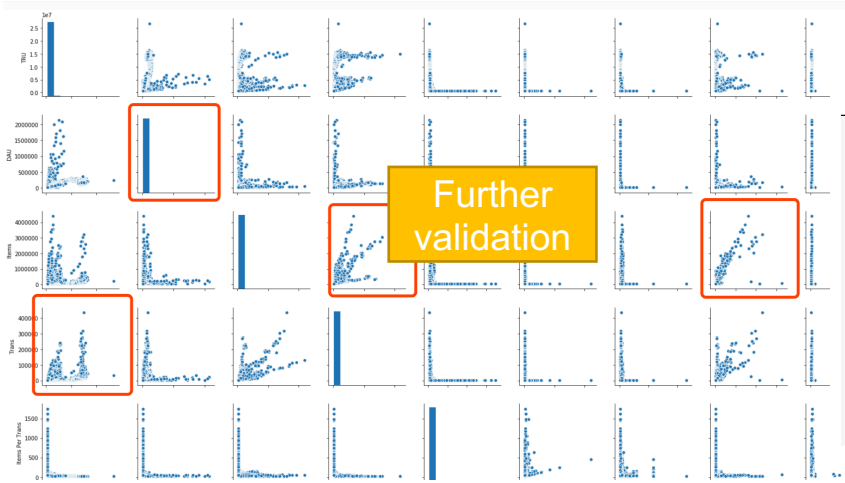
25%	6.288102e+05	1.529677e+04	4.342911e+04	3428.09000	17.580000	1.300000	2.300000	4537.010000	12.310000	98.950000
50%	6.314452e+05	1.537393e+04	4.352124e+04	3433.85000	28.090000	1.320000	2.560000	4532.770000	39.430000	118.180000
75%	6.574735e+05	1		3522.53000	36.080000	1.390000	3.000000	4611.080000	48.920000	139.370000
max	2.677675e+07	2		34846.58000	1744.870000	444.240000	232.630000	819825.280000	3912.090000	1390.060000

Remove

Further validation



Further validation

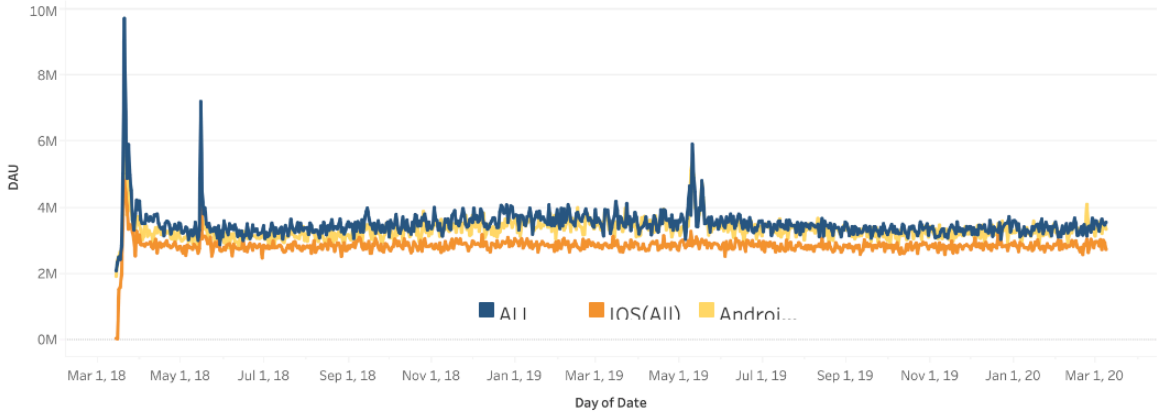
Country	Date	Platform	TRU	DAU	Items
	2018-03-16	4	4	4	4
	2018-03-19	5	5	5	5
	2018-03-2			5	5
	2018-0 22			5	5
	2018-03-23	5	5	5	5
Dominica	...	...	...	...	...
	2020-03-05	6	6	6	6

Drop

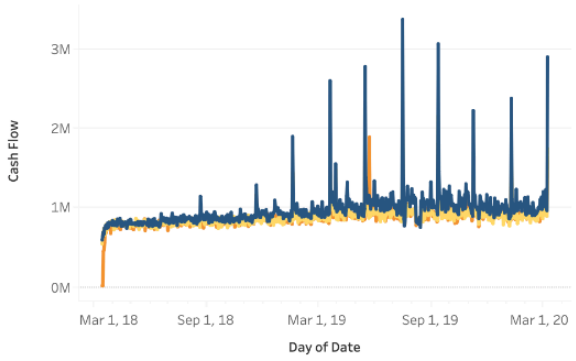
Business Dashboard

Overview of Key Performance Metrics

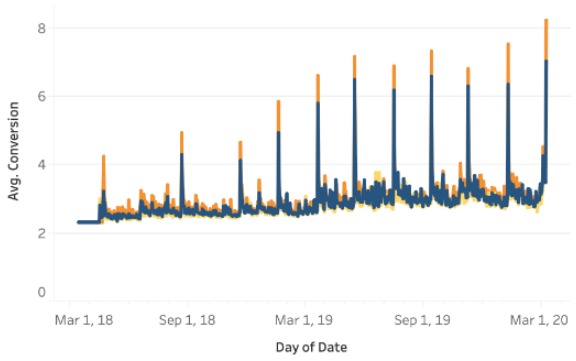
Total DAU Over Time



Total Cash Flow Over Time



Avg Conversion Over Time



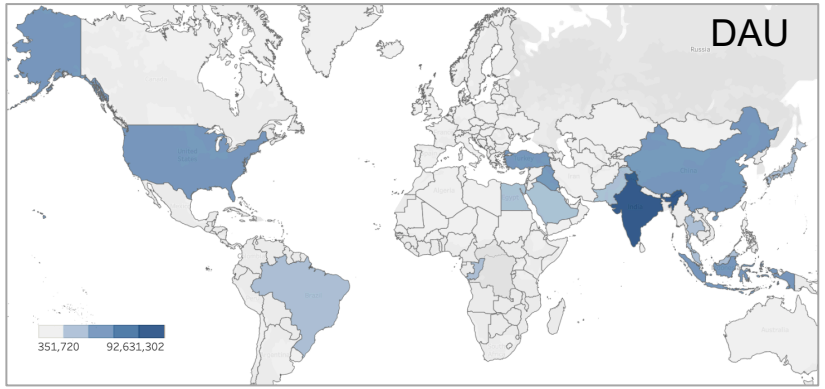
Observations

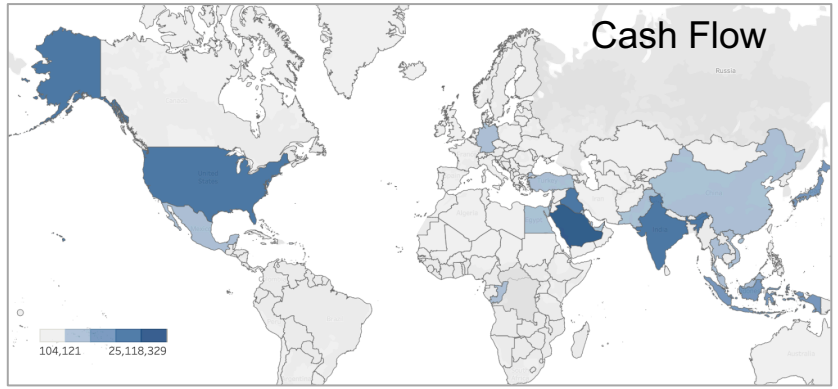
Total DAU Today	Avg Conversion % Today	Total Cash Flow Today
9,569,579	7.147	6,245,403

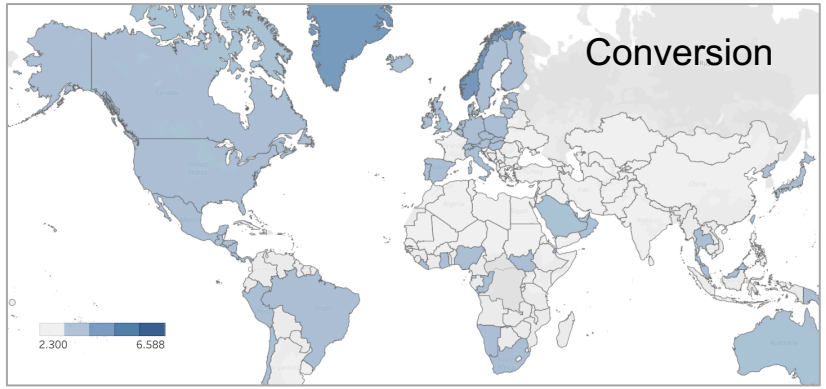
- Key Business Metrics
  - Normal level DAU for a half year
  - Excellent Cash Flow & Conversion
  - CF & Conversion peaks occur bi-monthly
- Platform Comparison
  - Three platforms shared similar **patterns** and **metrics**
  - All != iOS + Android (may be other platforms)
  - Cash Flow ~ Conversion starting Nov 2018
  - DAU: All>Android>iOS
  - Cash Flow: All>Android~=iOS
  - Conversion: iOS>All>~Andorid

Business Dashboard

Overview of Key Performance Metrics





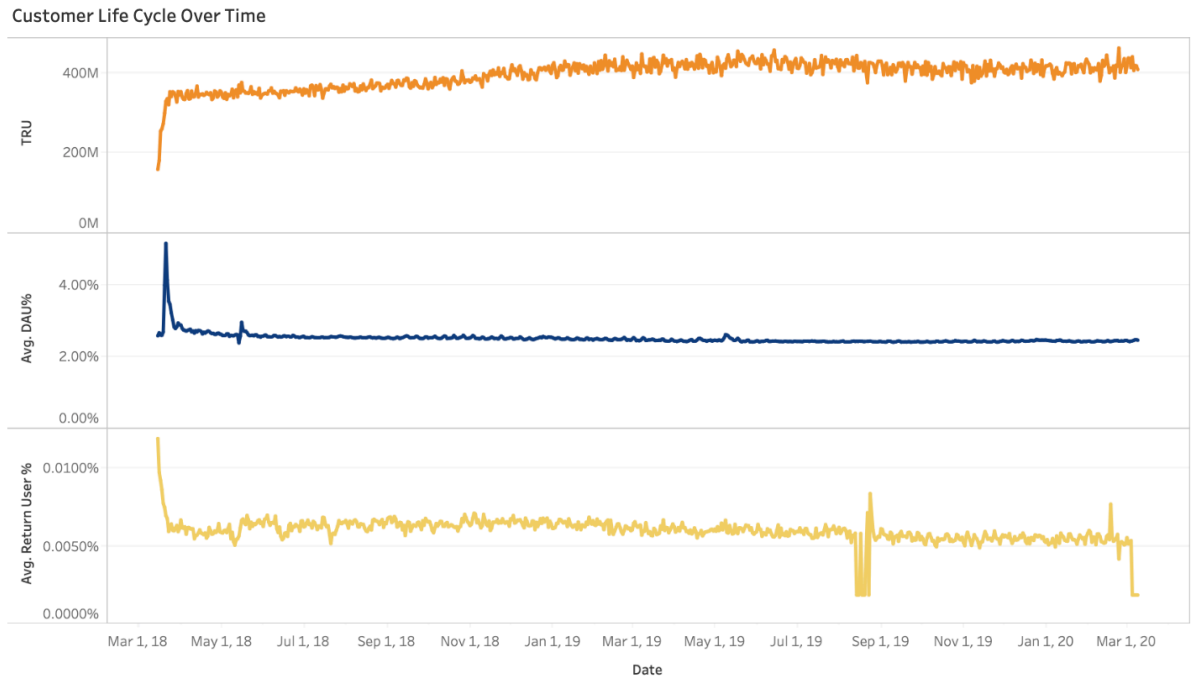


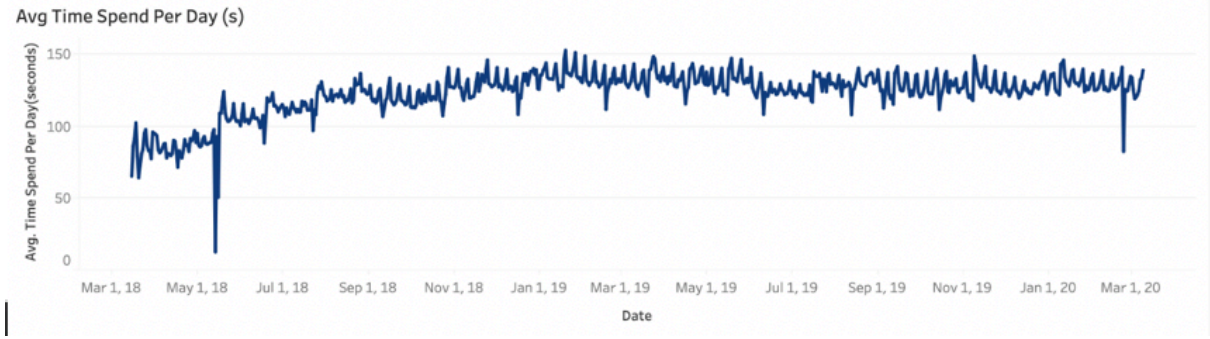
Observations

- Distribution: DAU~Cash Flow
- High DAU/CF countries: along roughly the same latitude
- High conversion countries: distributed by continents: North/South America, Europe, Ocenia

Business Dashboard

Customer Life Cycle



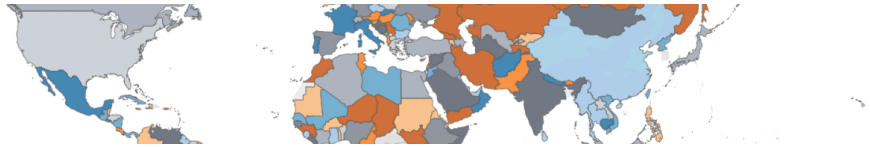


Observations

- Starting point: Highest return user, lowest TRU. When DAU increase, return user decrease.
- Growth: No obvious user acquisition after first launch
- Steady DAU over time
- Drop of time spend per day on around 15th of every month

Future work

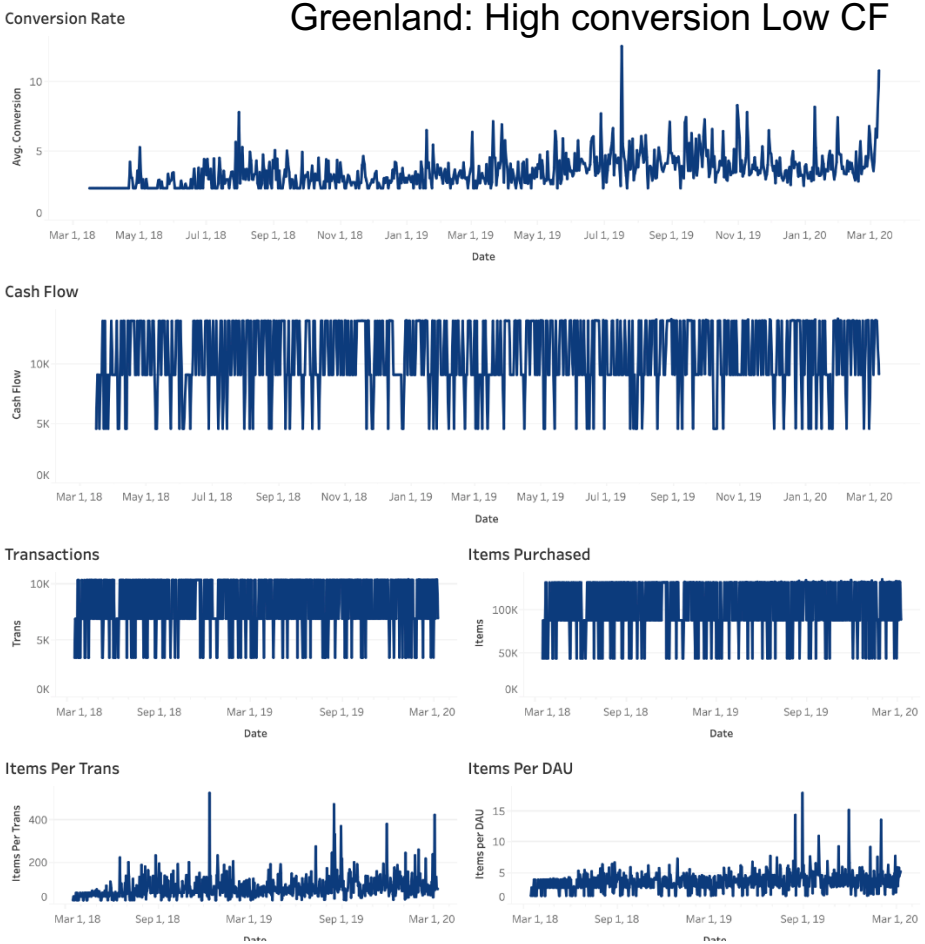
- Analyze the plot by countries using the map



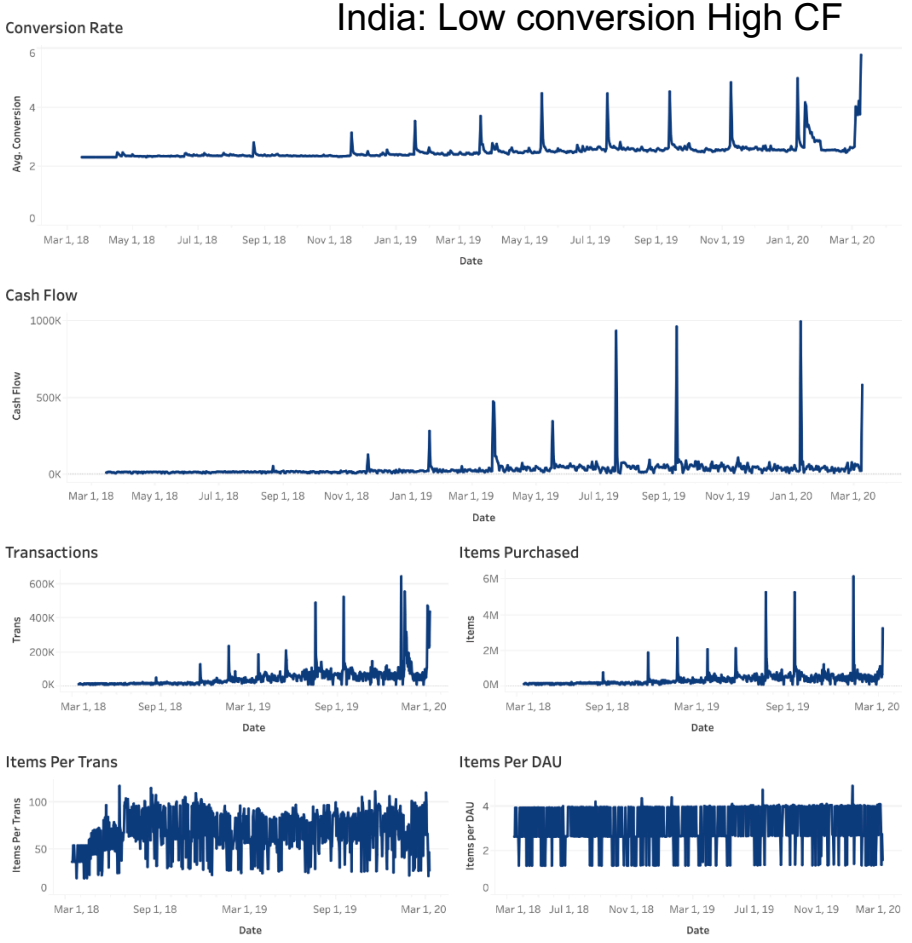
Business Dashboard

In-App Purchase

Greenland: High conversion Low CF



India: Low conversion High CF



Observations

- India:
  - Conversion bimonthly
  - Large cash flow when converse
  - Less items bought
- Greenland:
  - Low but continous cash
  - More items bought

Future Work

- More country comparisons

How’s the Current Business?

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- **Periodicity**:
  - There might be some campaigns/promotions that occur once every two months, which are very effective in conversion and attract people to purchase.
  - However, this campaign does little on attracting new customers/retention customers/daily active users.
- **Users**: High(low) conversion low(high) cash flow countries may relate to the per capita income.
  - In western countries where per capita income is high, on average people are willing to spend money on games and purchase more items
  - In countries where per capita income is relatively low but having a small group of wealthy residents, on average people may purchase less but a small number of people would like to purchase “luxurious items” in game as a reflection of their lifestyle
- **Game**:
  - The game may convert from an old version as it started from higher return customer
  - The game has remained the same registration user for over a year. It might have been taken off from the app store, and DAU are very sticky loyal users.

Contextual Anomalies

K-Means Clustering ✔

Within-cluster Isolation Forest

Data Wrangling

- **Datetime**: dayofweek, dayofmonth, month, year
- **Categorical**: “Country” into dummies and drop 1 column
- **Categorica**l: “Platform” into dummies and drop 1 column

Result:

- 252 columns in total

Find the Best K

- **Assumption** from previous steps
- **Elbow method**: compute within-Cluster-Sum of Squared Errors (WSS)

Result:

- Selected k=3 validated from both methods

Fit and Evaluate Model

- Kmeans(n_clusters=3, random_state=0).fit(X)
- Evaluation: compute silhouette_score

Result:

- Sihouette score > 0.91, excellent performance

Examine Clusters

- Attached labels to each records
- Subset clusters for later analysis

Result:

- # Cluster 1: 377101
- # Cluster 2: 774
- # Cluster 3: 5390

Contextual Anomalies

K-Means Clustering ✔

Within-cluster Isolation Forest

Data Wrangling

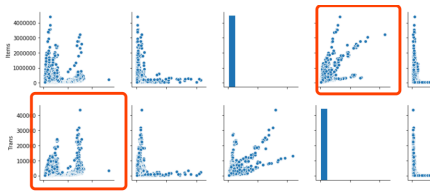
```
game_data.shape
```

```
(383265, 13)
```

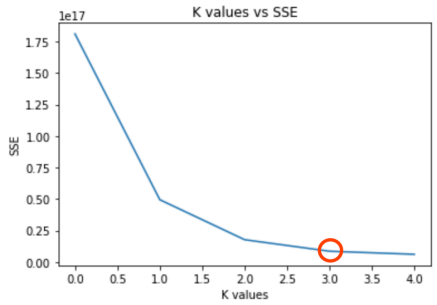
```
X.shape
```

```
(383265, 252)
```

Find the Best K



k=2/3



k=3

Fit and Evaluate Model

```
silhouette_score(X,
```

```
0.9194291375101088
```

Examine Clusters

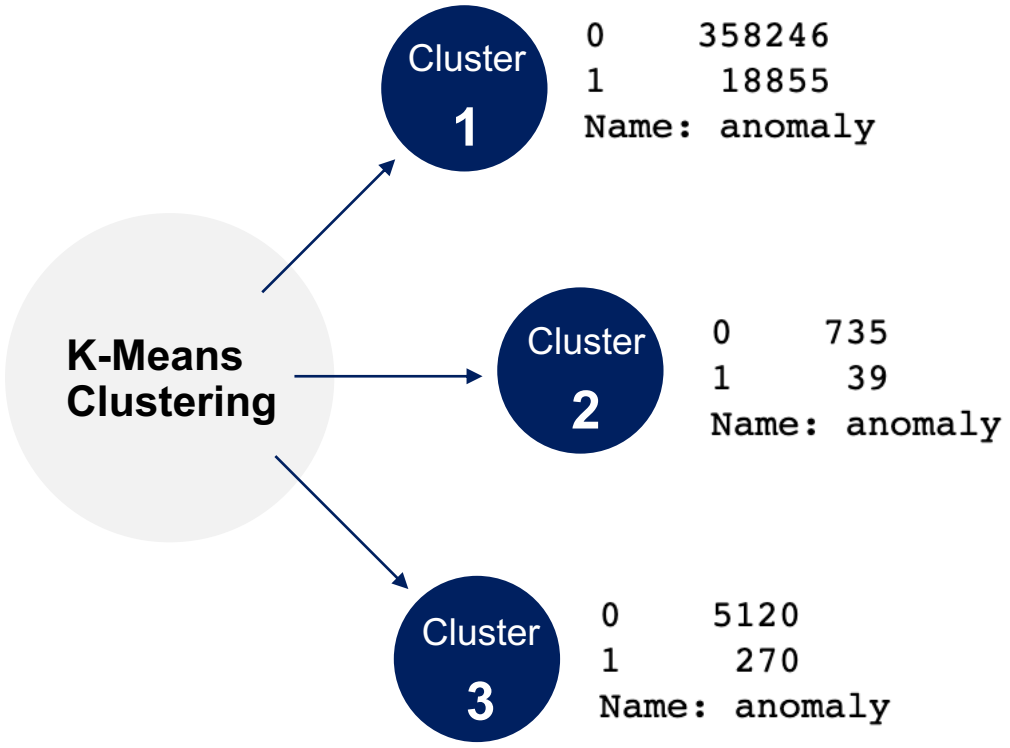
```
0    377101
2      5390
1       774
Name: label, dtype: int64
```

```
cluster1
cluster2
cluster3
```

Contextual Anomalies

K-Means Clustering ✔

Within-cluster Isolation Forest ✔



Within-cluster Isolation Forest

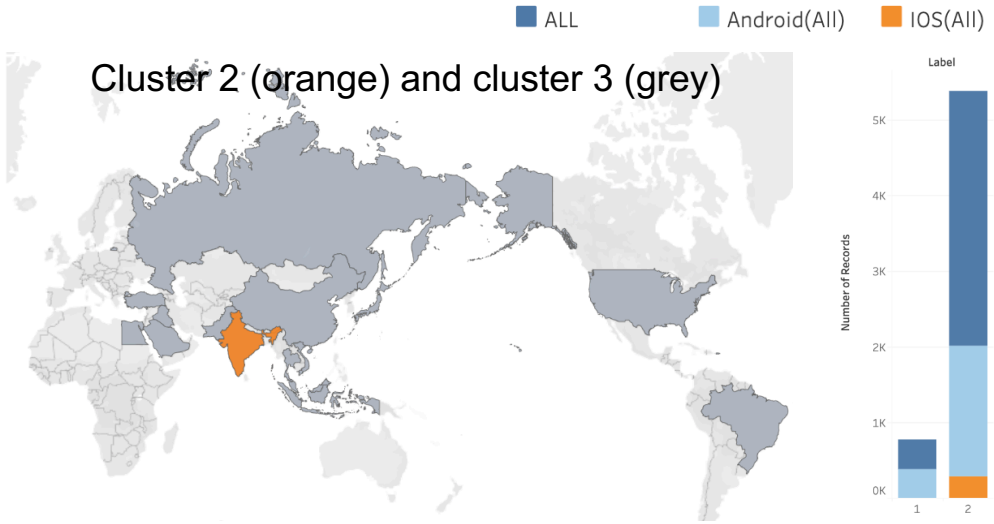
```
# input: 3 parameters
def isolation_forest(df, columns, outliers_fraction):
    data = df[columns] # extract data
    scaler = StandardScaler()
    np_scaled = scaler.fit_transform(data)
    data = pd.DataFrame(np_scaled) # scaled data

    model =  IsolationForest(contamination=outliers_fraction)
    model.fit(data) # train isolation forest

    # attach anomaly label
    # 0: normal, 1: anomaly
    df['anomaly'] = np.array(pd.Series(model.predict(data)))
    df['anomaly'] = df['anomaly'].map( {1: 0, -1: 1} )

    # return dataframe with anomaly label
    return df
```

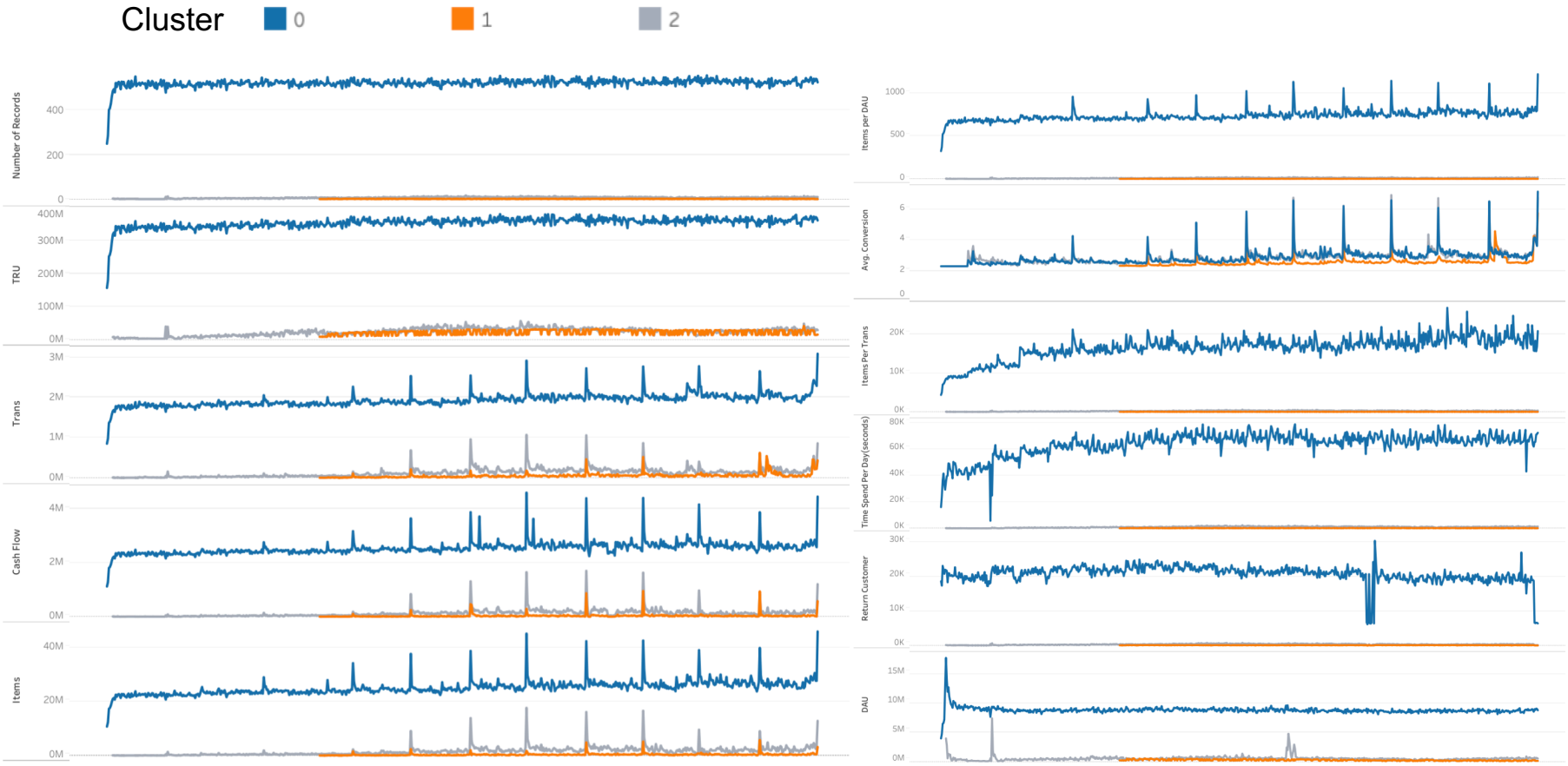
Cluster Characteriestics



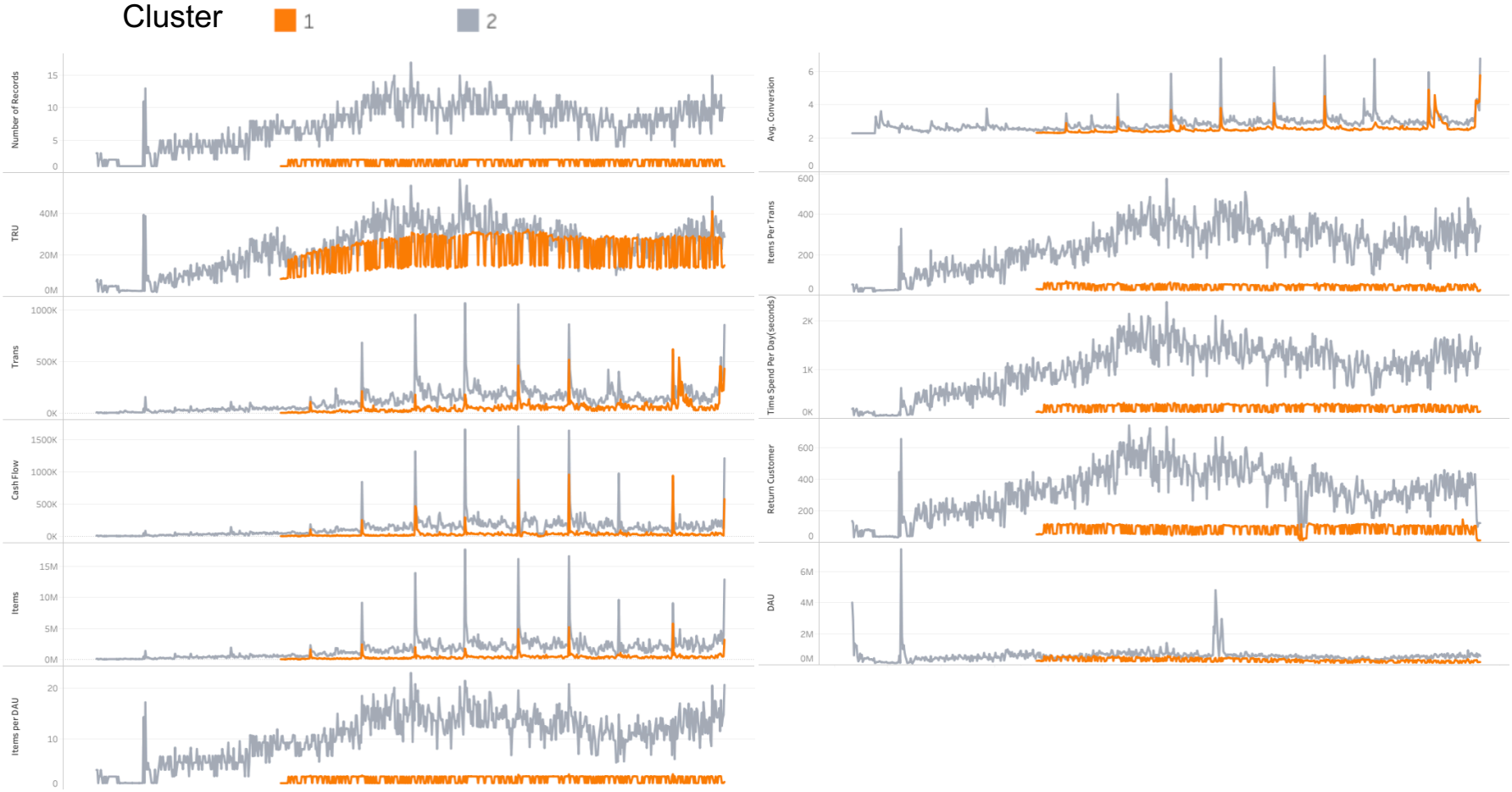
Observations

- Cluster1:
  - Worldwide
  - Evenly divided platforms
- Cluster2:
  - India
  - No iOS, evenly divided android/all
- Cluster3:
  - High DAU/Cash Flow country plus Russia
  - Platform All>Android>iOS

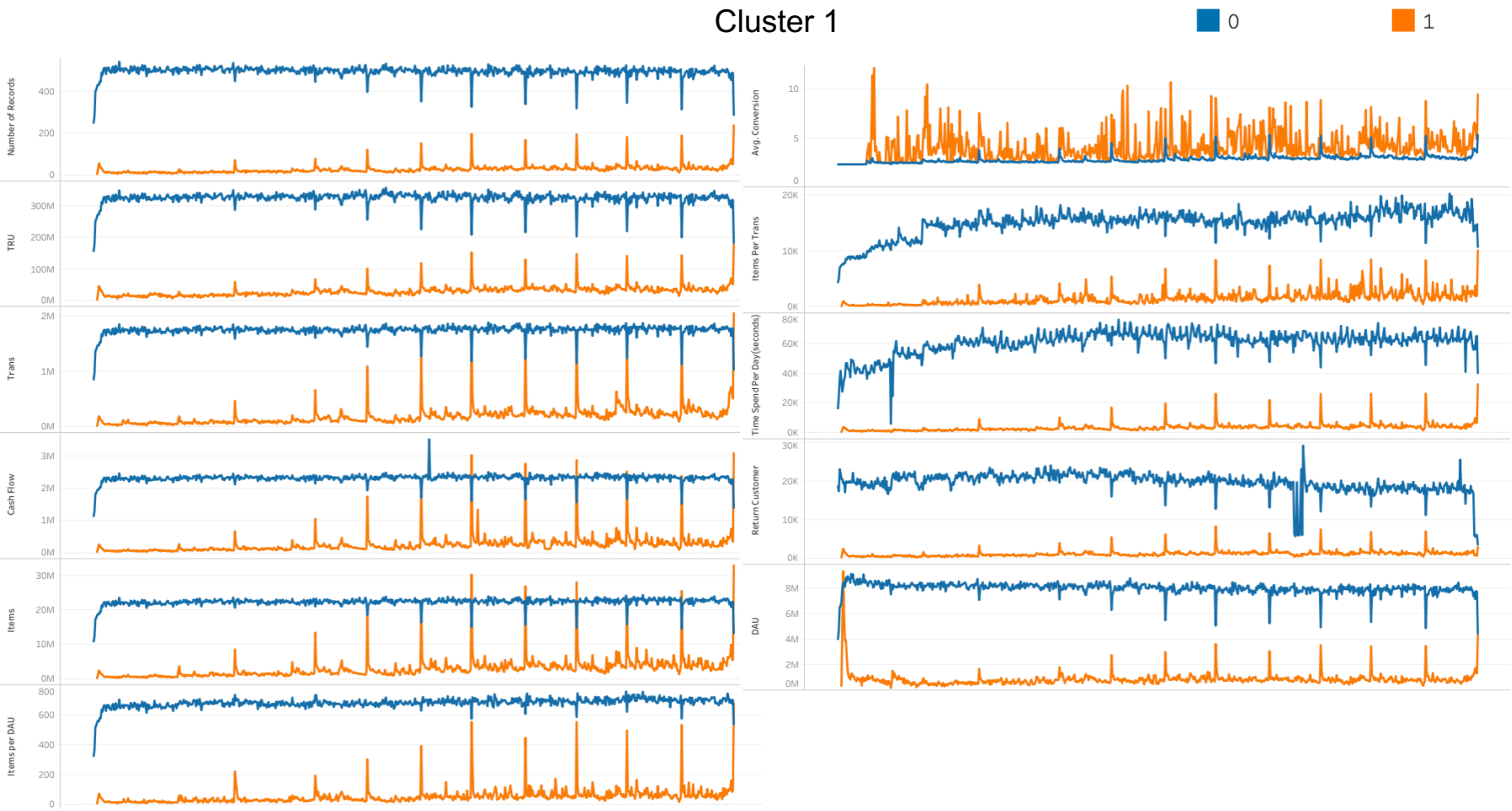
Cluster Time Series Analysis



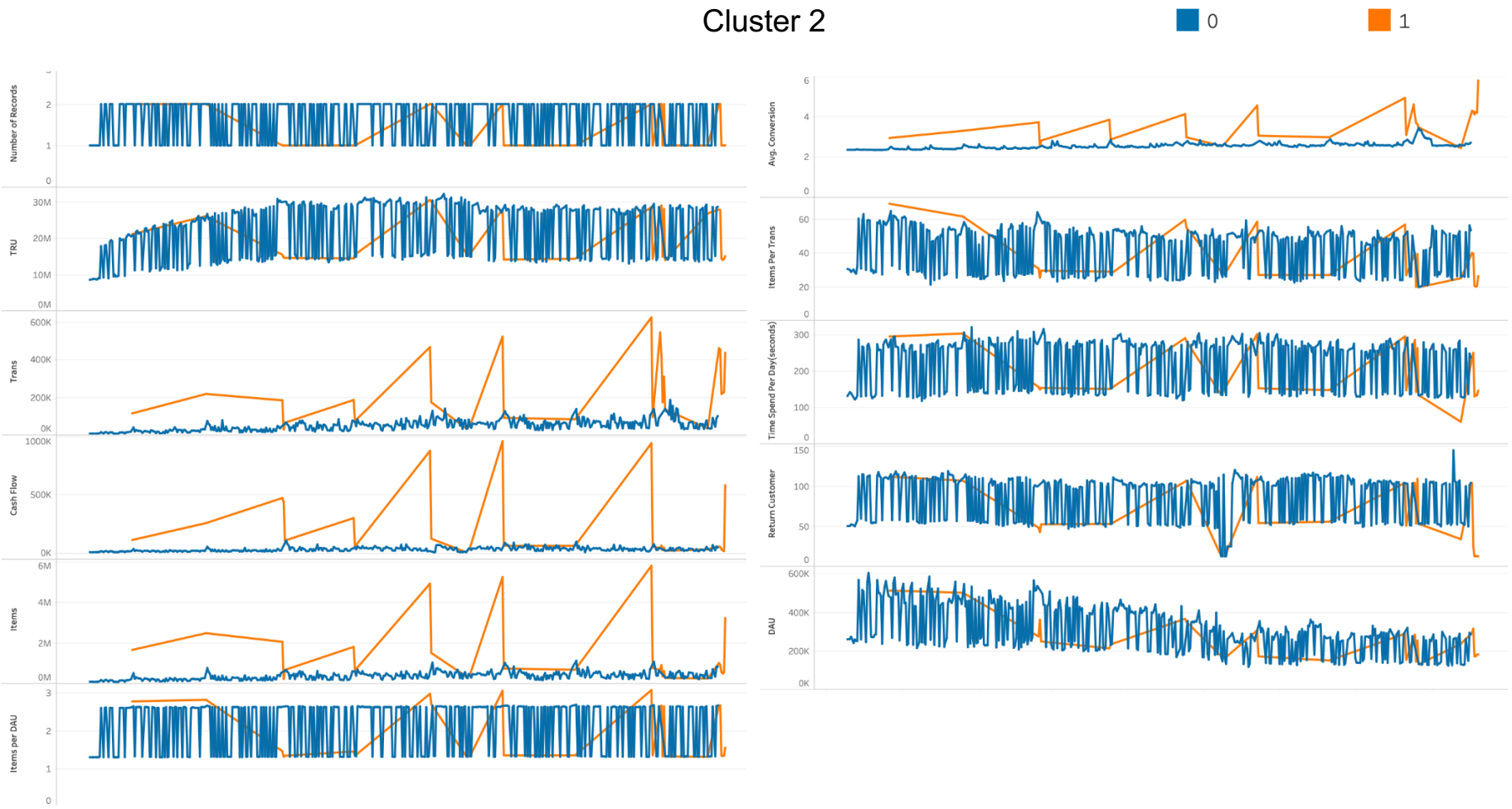
Cluster Time Series Analysis



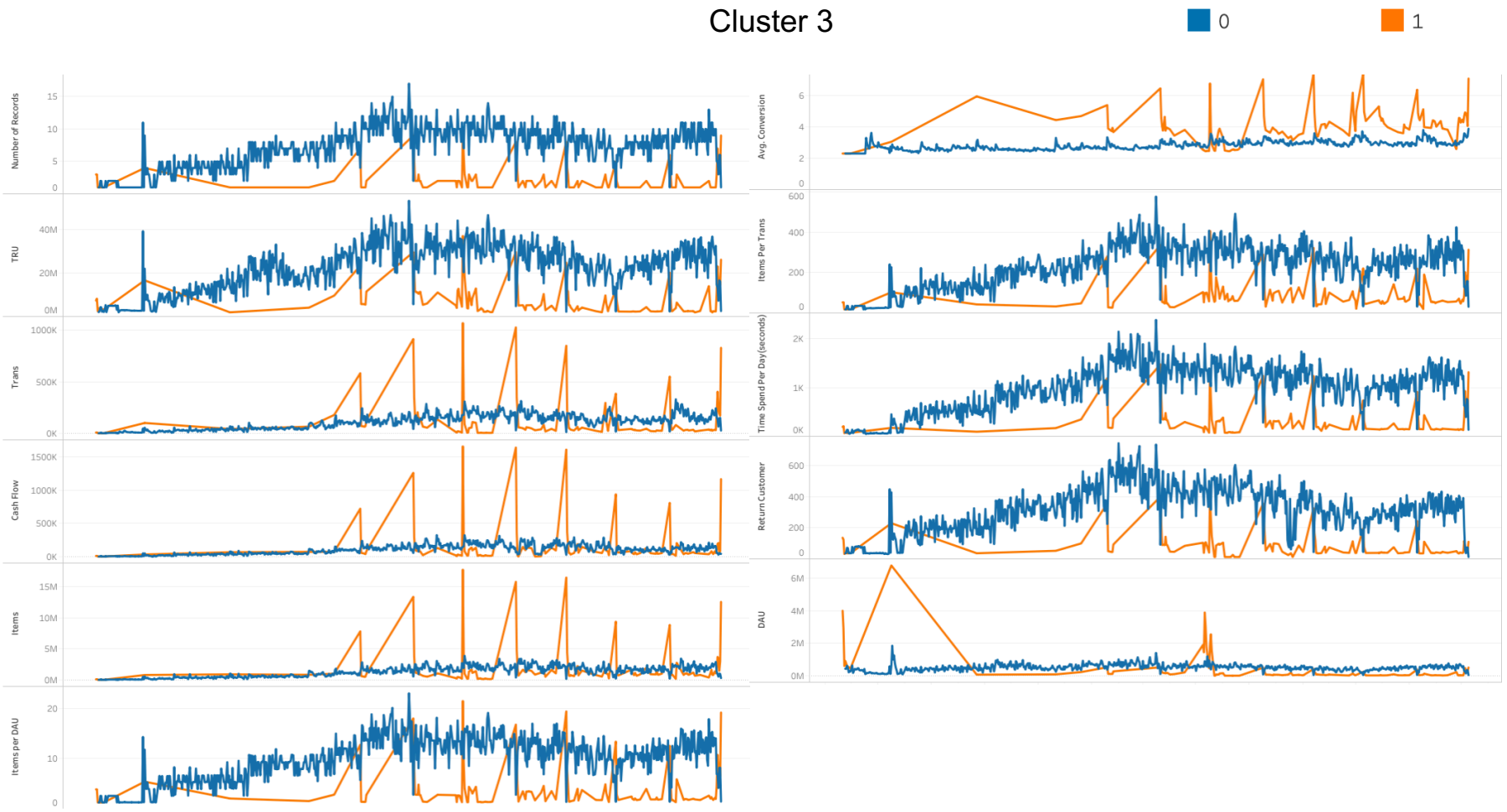
Anamoly Time Series Analysis



Anamoly Time Series Analysis



Anamoly Time Series Analysis



Next Opportunity?

- **Goal**s: Depending on the most urgent goals to be achieved, several strategies can be applied
  - **TRU/DAU and Conversion**
    - External market strategy: more promotions/consumer acquisition in North America/South America/Oceania/European countries, who are very willing to purchase items
    - Extension of the bimonthly campaigns: as it's effective in improving conversion rate
  - **Cash Flow**
    - Product innovation: improve the design and launch of luxurious items for in-app purchase
    - Localization: improve research on preferences of people from high cash flow countries
- **Segmentation:**
  - Cluster 2 tends to be less valuable as they are inactive and spend less
  - Cluster 3 tends to be potential return users that can be transformed into active users
- **Future work:**
  - More exploratory analysis on anomaly data points to examine the cluster characteristics


Tencent
THANK YOU