Group 15 is coming

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The three-step approach

What we did



At the end what does it mean...?

How we improved it

What we did

```
def clean(dummy, threshold):
   1 = []
   #just to index easily
   dummy = np.array(dummy)
   for i in range(dummy.shape[1]):
       #check how many stores per category
       1.append(np.sum(dummy[:,i]))
   l = np.array(1)
   col_to_keep = []
   #check if the category has more than threshold observations
   for j in range(len(l > threshold)):
       #take the category with highest number of stores
       if (l > threshold)[j] == True:
           #if enough add it into the list
           col_to_keep.append(j)
   return col_to_keep
```

Dummy Variables



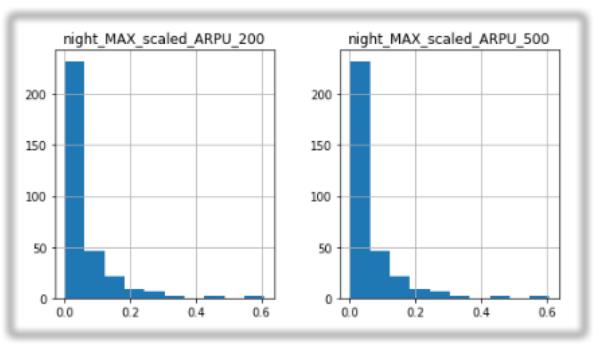
```
AVG1 = (data['night_MIN_scaled_ARPU_200'] + data['night_MAX_scaled_ARPU_200']) / 2

AVG2 = (data['midday_MIN_scaled_ARPU_200'] + data['midday_MAX_scaled_ARPU_200']) / 2

AVG3 = (data['weekend_MIN_scaled_ARPU_200'] + data['weekend_MAX_scaled_ARPU_200']) / 2

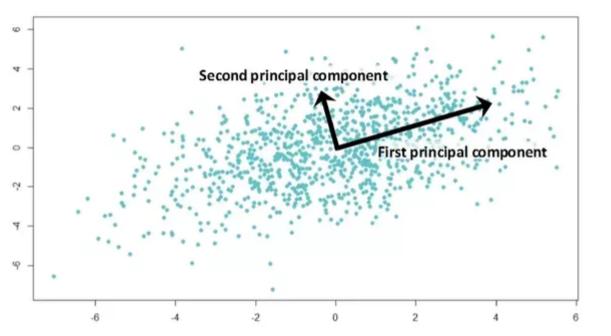
AVG4 = (data['night_MIN_scaled_ARPU_500'] + data['night_MAX_scaled_ARPU_500']) / 2
```

Average Min-Max ARPU



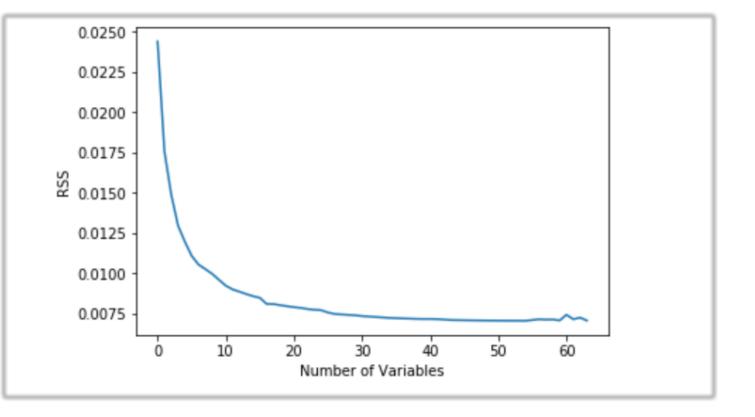
```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
pca = PCA()
X_train = pca.fit_transform(X_train)
X_test = pca.transform(X_test)
explained_variance = pca.explained_variance_ratio_
print(np.cumsum(explained_variance))
```





```
1) RSS = []
2) dataframe = []
3) for feature in features:
       model.fit(dataframe + feature, y)
       SS = np.sum(y - f(x)**2)
       RSS.append(SS)
4) feature = np.argmin(RSS)
5) dataframe.add(feature)
6) drop feature from features
7) go back to 3
```

Forward Selection

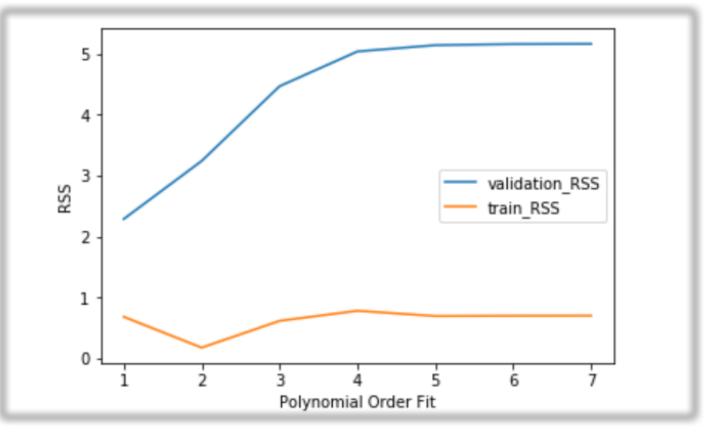


Linearity

```
y_pred = model.predict(datadf)
y_squared = pd.DataFrame(y_pred**2)
y_third = pd.DataFrame(y_pred**3)
merged_df = pd.concat([datadf, y_squared, y_third], axis = 1)
model = LinearRegression()
model.fit(merged_df, y)
y_merged = model.predict(merged_df)
RSS_restr = np.sum((y_pred - y)**2)
RSS_unr = np.sum((y_merged - y)**2)
j = 2
F_test = ((RSS_restr - RSS_unr) / j) / (RSS_unr / (322 - 6 - 1))
Critical_value = 4.667
print(F_test)
4.036142316552256
```

Overfitting

Tests



Choose one model and optimize its hyperparameters by Grid search

- Brute-Force Approach
- Try all the possible combinations
- Get the lowest RSS

```
C_values = [50, 55, 60, 70,100, 105,110,115,120, 200]
gamma_values = [0.01, 0.03, 0.1, 0.2, 0.11, 0.15, 0.25, 0.3, 0.09, 1, 10, 100]
best_RSS_test = 1000
best_params = {'C': None, 'gamma':None}
for C in C_values:
    for gamma in gamma_values:
        model = SVR(C = C, gamma = gamma, cache_size = 7000)
        model.fit(x_A, y_A)
        predictions = model.predict(x_B)
        RSS_test = np.sum((y_B - predictions)**2) / x_B.shape[0]
        if RSS_test < best_RSS_test:</pre>
            best_RSS_test = RSS_test
           best_params['C'] = C
            best_params['gamma'] = gamma
print(f'best RSS test = {best_RSS_test}')
print(best_params)
```

How we improved it

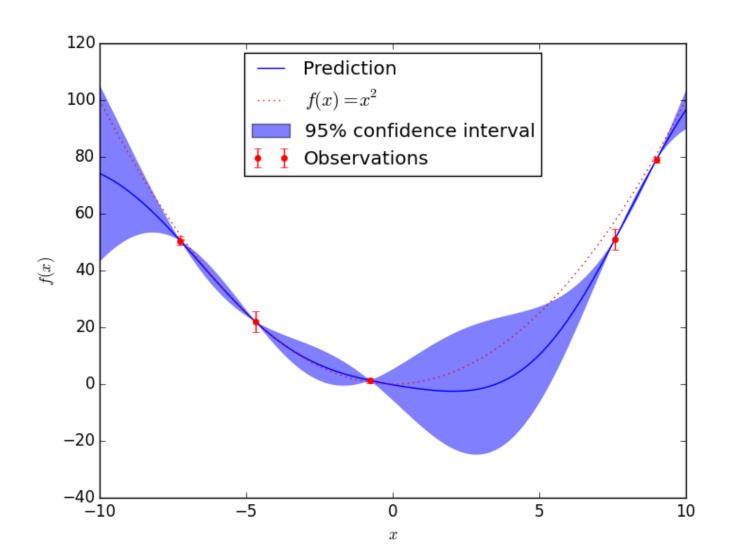
Bayesian optimization approach

UPDATE CURRENT BELIEFS EVALUATE THE LOSS FUNCTION PERFORMACE WITH NEW PARAMETERS

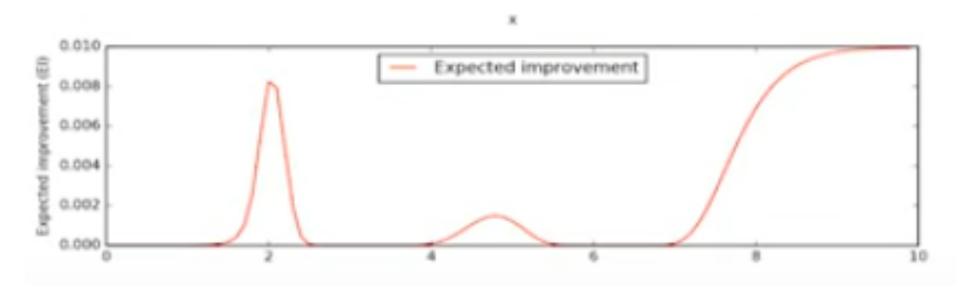
CHOOSE PARAMETERS
THAT MAXIMIZES UTILITY
FUNCTION OVER
CURRENT BELIEFS

Loss function modeled with Gaussian Processes

- A Gaussian process generates Functions instead of Random Variables
- Returns mean and Variance of a Normal distributions over all possible values of f at x



Next Hyperparameter through Expected Improvement Function



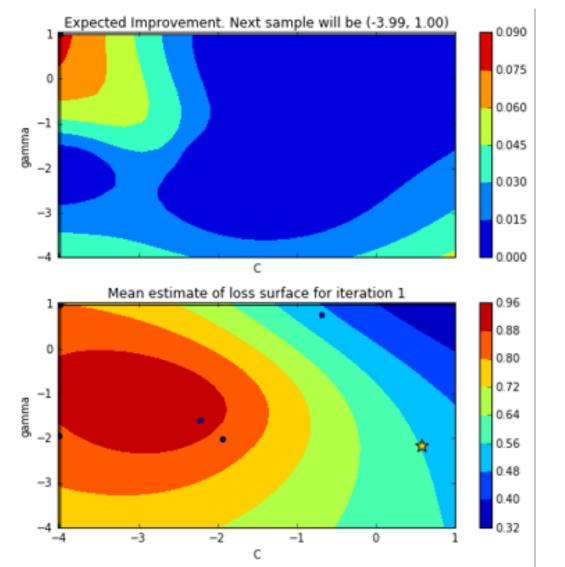
$$EI(\theta) = \mathbb{E}[\max_{\theta} \{0, f_{\mathcal{M}}(\theta) - f_{\mathcal{M}}(\hat{\theta})\}],$$

$$\theta_{new} = \arg\max_{\theta} EI(\theta)$$

Next Hyperparameter through Expected Improvement Function

$$EI(\theta) = \begin{cases} \left(\mu(\theta) - f(\hat{\theta})\right) \Phi(Z) + \sigma(\theta) \phi(Z), & \sigma(\theta) > 0 \\ 0, & \sigma(\theta) = 0 \end{cases}$$

$$Z = \frac{\mu(\theta) - f(\hat{\theta})}{\sigma(\theta)}$$



The results

```
23
0.009202683468072811
[5.50006865e+01 3.14685669e-02]
```

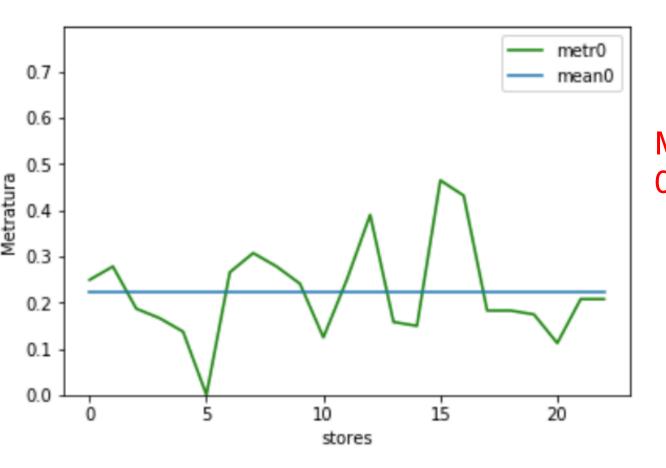
```
model = SVC(gamma = best_params['gamma'], C = best_params['C'])
model.fit(X_train, y_train)
predicted_classes = model.predict(X_test)
accuracy = accuracy_score(y_test,predicted_classes)
print('accuracy svc= ',accuracy)
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
print(confusion_matrix(y_test,predicted_classes))
print(classification_report(y_test,predicted_classes))
accuracy svc= 0.7076923076923077
[[11 6 0]
 [7145]
 [0 1 21]]
                         recall f1-score support
            precision
                           0.65
                           0.54
                 0.81
                           0.95
                                    0.88
                                                22
                                    0.70
                                                65
avg / total
                 0.70
                           0.71
```

At the end what does it mean...

Results are not the end, but the beginning...

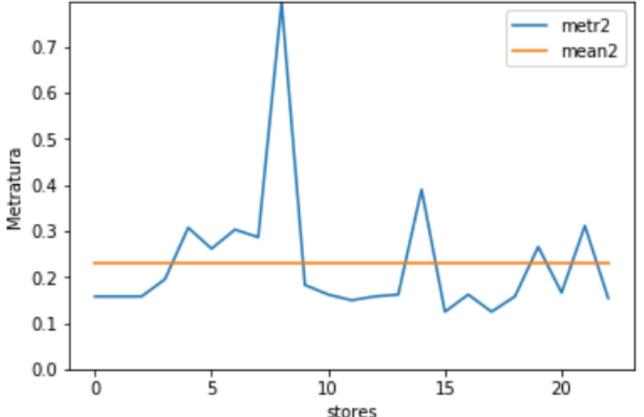
Compare stores with high footfall against low footfall...to give business solutions!

Metratura 0 vs Metratura 2

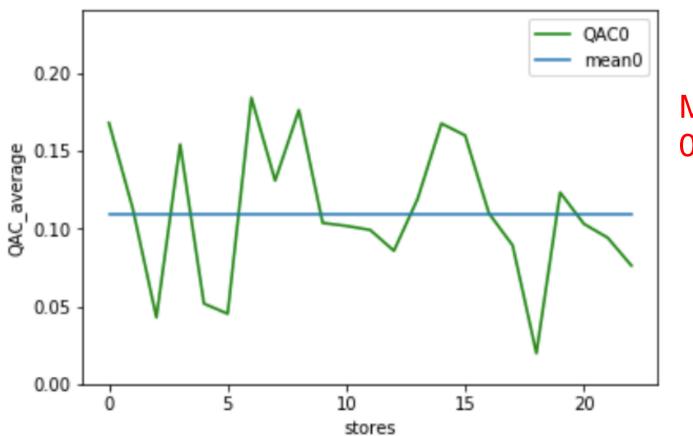


Mean_Metratura_0 0.213335

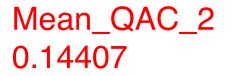
Mean_Metratura_2 0.230019

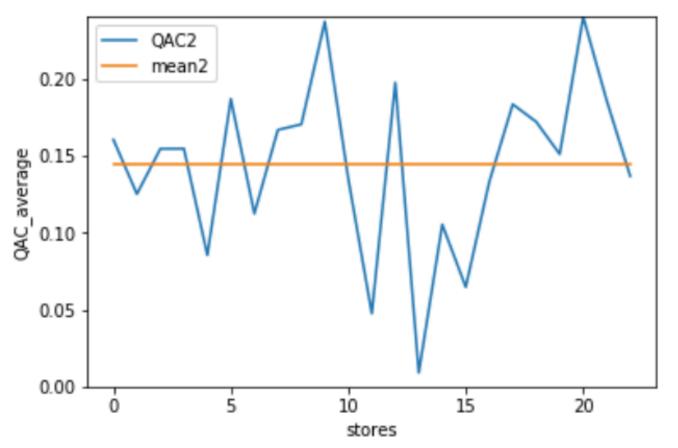


QAC 0 vs QAC 2

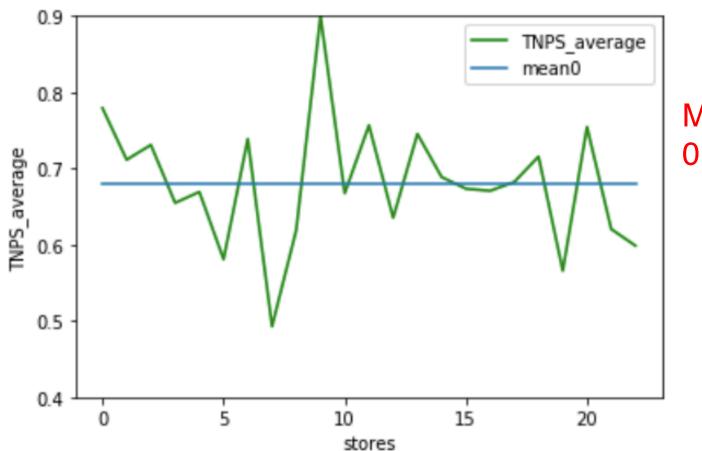


Mean_QAC_0 0.1098

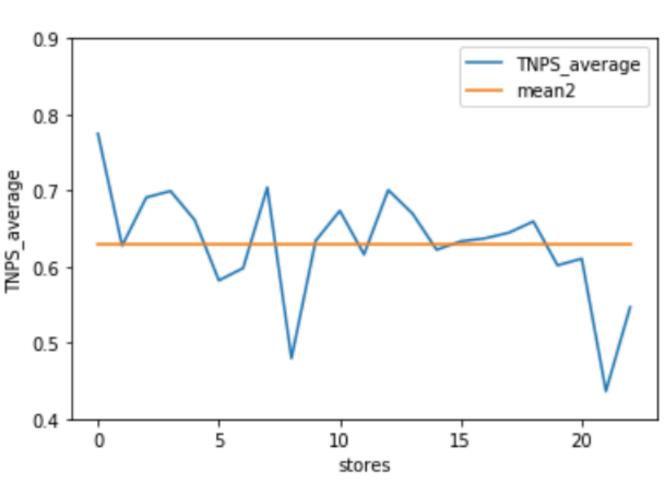




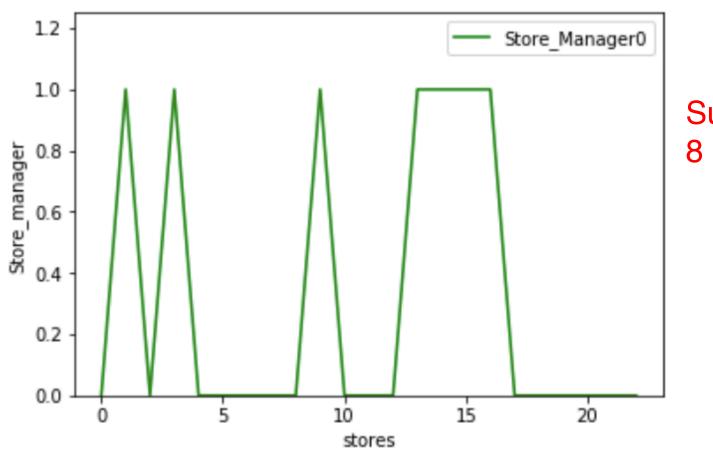
TNPS 0 vs TNPS 2



Mean_TNPS_0 0.692260 Mean_TNPS_2 0.6305

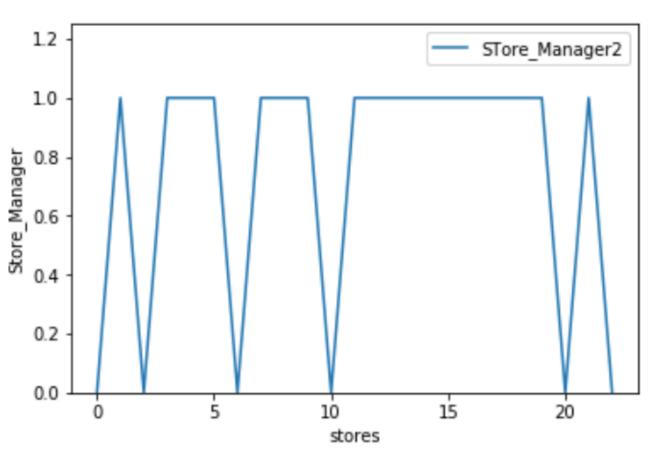


Manager 0 vs Manager 2

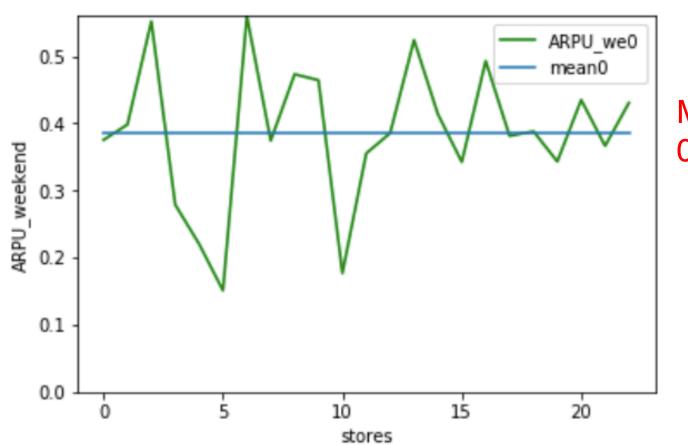


Sum_Manager_0 8

Sum_Manager_2

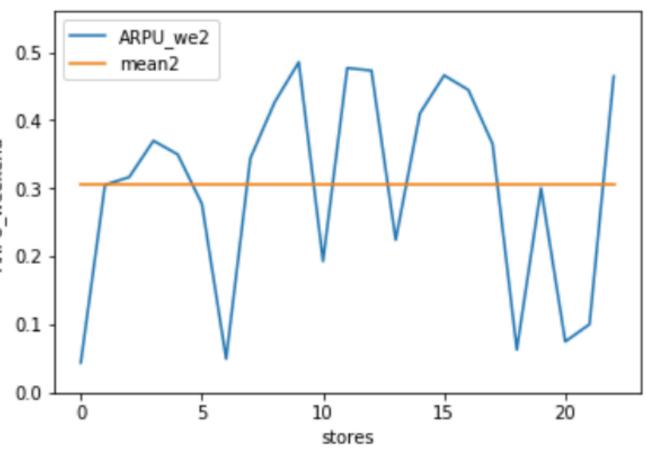


ARPU_WE 0 vs ARPU_WE 2



Mean_Weekend_ARPU 0.305503

Mean_Weekend_ARPU 0.386400



Suggested Business Solutions

- 1. Don't increase Vodafone Store square meters
- 2. Increase Number of tickets opened for Phone Assistance
- 3. Don't put too much attention on the grade/opinion on stores of VF customer
- 4. Promote more Store Managers
- 5. Work on increasing Weekend ARPU!

Thank you!